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It's in the Way You Move: The Effects of Surface Luminance and Texture Discontinuities on Object-Reachability Revealed by Head-Motion in Virtual Reality

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It’s in the way you move: The effects of surface luminance and texture discontinuities on object-reachability revealed by head-motion in virtual reality.

by

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ABSTRACT

Perceiving distance is at the heart of everyday actions like reaching for a cup of coffee. This action may depend on the biomechanical restrictions of the actor (arm-length), the physical distance of the cup, and environmental variables such as surface luminance and texture. Four experiments were conducted to investigate the roles of two environmental variables (surface luminance and surface texture discontinuities) and two movement variables (average magnitude head displacement and the multifractal structure of head motion) in the perception of object reachability in virtual reality. Results suggest that surface texture discontinuities and overall surface luminance affect reaching judgments in different contexts, with exploration patterns modulating each effect. Luminance was a stronger factor than discontinuity, and average magnitude head displacement modulated the effects of the environmental variables more than multifractality. In complex stimulus conditions, dynamic parameters (e.g., movement) predicted perceptual responses above and beyond static parameters alone. In addition, the temporality of environmental variables appears to influence the modeling of the perceptual response based on the conjecture that discontinuity is necessarily explored over time and space, whereas homogeneous luminance does not have to be. In the context of reaching tasks in virtual reality, more movement appears to generate richer optic structure helping to reveal the effects of surface texture variables in judging object reachability.

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DEDICATION

This work is dedicated to my parents, John and Mary Doyon. I will never be able to adequately express my love and gratitude. Only with their tireless support and encouragement was I able to come this far. I love them infinitely and I will be forever thankful for their love and support.

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CHAPTER I - INTRODUCTION

Questions about the nature of perceptual information occupy many vision scientists. We may colloquially refer to information and information-processing, but rarely do we address the question of what information is. For some, information is merely that which stimulates some sense organ, such as photons (for vision), molecules (for olfaction and gustation), or mechanical reverberations (for audition and haptic perception). For others, information is the patterning of that which stimulates the sense organs, such as how the light is scattered on and around objects and surfaces, or how intervals between reverberations vary in length over time. In this sense, the information is not the physical manifestation of some stimulus, but rather those patterns that are invariant across transformations of time and scale. For example, human observers can detect biological motion in point-light displays only by perceiving the invariant relationships between the elements' movements over time (Runeson & Frykholm, 1983). Humans can also discriminate between similar events depending on the structuring of the sounds created by a glass bottle dropping from a table, where the event of the bottle breaking is characterized by asynchronous and irregular reverberations, while the event of the bottle bouncing is characterized by synchronous, regular sounds (Warren & Verbrugge, 1984).

The latter approach to explaining the nature of information was first proposed by J.J. Gibson (1950). For Gibson, the information for perception exists in higher-order variables and patterns present in lawfully structured energy arrays. This claim would go on to become one of the central theoretical arguments in his *Ecological Approach to Visual Perception* (Gibson, 1979). This approach differs from traditional approaches in that it treats perception as "direct". Higher-order informational variables contained in lawfully structured energy arrays are detected and perceived in an "online" manner, without cognitive mediation, such as embellishing an impoverished retinal image (see Neisser, 1967). Gibson's approach suggests that percepts are specified in a lawful 1:1 mapping of information in the environment to perceptual experience in the observer. For example, an observer will have the visual experience of backward motion as the visual world contracts from the periphery in to the fovea as when the observer gazes out to the horizon from the back of a moving train. This visual contraction, known as optic flow, is the higher-order informational variable contained within the lawfully structured optic array, which specifies the event of moving backwards.

Structuring of Light in the Optic Array

According to Gibson, the information for vision is in the light, i.e., information is characterized by how ambient light is structured by the scattering, reflection, and refraction of light caused by surfaces and objects (1950). Projected from a source (sun, lamps, screens, etc.), light becomes structured uniquely to the current layout of objects and surfaces. As a person moves through the illuminated environment, light bounces and scatters on and around his or her body causing a cascade of subtle structural changes to the ambient light in the environment. Similarly, if one were to shift around tables, chairs, and coffee mugs in an office space, the structural changes to the ambient light of the office environment necessarily entail as well. It follows then that a particular structuring of the ambient light is specific to a particular configuration of observers, surfaces, and objects. Further, a particular structuring of light should also specify the presence or absence of an object as the two are causally related. If this is the case, then the structuring of the light should also interact with other stimulus arrays in the service of accomplishing some action within the constraints of the environment; that is to say, the structuring of the light should carry consequences for action revealed through its interactions with additional stimulus arrays, e.g., the proprioceptive stimulus array that specifies perception of the body and its positioning in space.

Information in the Extended Global Array

Gibson's proposal concerned singular arrays of energy that structure informational variables for each of the perceiver's sensory systems, i.e., an optic array for vision, chemical arrays for olfaction and gustation, an acoustic array for audition, and a mechanical array for haptic perception (1950). However, this overlooks important multimodal relationships which are both available and detectable to the perceiver. These multimodal relationships contain important interactions between individual arrays which can specify unique perceptual events that are not possible when relying on just one array in isolation. For example, the McGurk effect (McGurk & MacDonald, 1976) is an audiovisual illusion where an observer is presented a video recording of a person repeating the sound "fah" while the audio stream has been replaced with the same individual instead saying "bah". Observers tend to report one of three perceptual outcomes: (1) correctly perceiving the auditory stimulus as "fah", (2) incorrectly perceiving the auditory stimulus as "bah", or (3) some combination of the two stimuli. This illusion arises when the information that is structured by the optic and acoustic arrays specify two unique events (in this case, the aural percepts "fah" and "bah", respectively), yet are presented to the observer simultaneously. While this is a perceptual illusion[1], the McGurk effect highlights the dependence of multimodal perception on the interactions of more than one stimulus array.

This relationship between multimodal perception and the interactions of different energy arrays was formally addressed by Stoffregen and Bardy (2001) in their proposal of a higher-order global array which spans the singular energy arrays (e.g., optic, acoustic, etc.). In the case of the McGurk effect, the illusory percept is specified in the global array where the perceptual systems sample from one united energy array which contains specific patterns of physical energy in the light and in the sound. While being a significant step toward an all-encompassing characterization of information for the perception-action cycle, Witt and Riley (2014) suggested that the global array must be extended to accommodate for interoceptive energy arrays in addition to the traditionally considered exteroceptive energy arrays. This extension reaches into the perceiver to consider arrays of chemical energy, mechanical energy, and behavioral energy which has been shown to specify perceptual events that appear to contradict the ecological direct-perception hypothesis, i.e., that perception occurs without cognitive mediation (for a review of action-specific effects, see Witt, 2011). Internal states such as fatigue, energetic potential, and body morphology are specified in stimulus arrays composed of chemical distributions of glucose (hunger), lactic acid (fatigue), or adenosine triphosphate (ATP; energetic potential) have the potential to modulate visuoperceptual experiences such as estimating steepness or distance as being steeper or farther when fatigued, despite identical optical arrays. Accordingly, an individual's perceptual experience necessarily depends not just on exteroceptive energy arrays, but also interoceptive energy arrays and the interactions between both.

The Optic Array in Virtual Reality

If, then, an individual's perceptual experience depends on the entire set of stimulus arrays spanning both exteroceptive and interoceptive energy arrays, what perceptual consequences might occur when one of the primary stimulus arrays, the real-world optic array, is replaced with a simulation? Virtual reality systems provide the opportunity to do just that: replace the real-world optic array with some simulation of a real environment.

Research concerning perceptual processing in virtual environments has seen a rapid expansion over the past two decades and show only signs of expanding further. While there are many technical concerns where human-computer interfaces are involved in perceptual investigations such as issues in rendering large depth intervals of three-dimensional visual space using only two-dimensional projections in the head-mounted device (Wann, Rushton, & Mon-Williams, 1995) and issues regarding the compression of estimates of distance and depth (Armbrüster, Wolter, Khulen, Spijkers, & Fimm, 2008; Thompson et al., 2004; Creem-Regehr, Willemsen, Gooch, & Thompson, 2005), relatively little attention has been directed toward investigating perception-action processes from an ecological point of view in virtual reality systems . By asking individuals to sample from the real interoceptive stimulus arrays (e.g., body morphology, intentions, and energetic potentials), while also sampling from the simulated optic array generated by a virtual reality system, this work should reveal any potential interactions between real and artificial stimulus arrays that may arise in action-related perceptual processes. The case may be that the visual information specified by the simulated optic array is an adequate approximation of the real-world optic arrays seen in everyday perception (e.g., Interrante, Ries, & Anderson, 2006); and if this is the case, then the ecological principles of visual perception in service of action outlined by Gibson (1979) should hold true. However, the case may be that the artificial optic array does not adequately approximate the real-world structuring of light seen in everyday perception, and as a result, it may differentially affect the visual perception of action possibilities.

The Detection of Information

Though information may be structured in lawfully governed interactive energy arrays, such information means little to the perceiver if he or she is unable to detect that information. The reader may be familiar with the question of the ontology of perceptual events first posed in 1710 by George Berkeley (1907) that was later colloquialized as a question of whether a tree falling on an island absent of an observer would make any sound (Chautauquan Literary and Scientific Circle, 1883). While the physicist might say, "Of course the tree makes a sound because sound is the result of mechanical perturbations in the physical medium, air," he or she cannot say that the sound is perceived. This is what Gibson referred to as a potential stimulus (1960), where some physical energy is capable of stimulating one of the sensory systems, but is unavailable, inaccessible, or occurring at a scale not relevant to the observer. Additionally, the environment is incredibly rich with to-be-detected information, so much so that the observer would be overwhelmed by such immense stimulation. Accordingly, the perceptual systems seek out information selectively according to the constraints of a given action. Selective attention is a mechanism that has been widely studied by perceptual psychologists, and it is the mechanism by which perception serves action, guiding the sensory systems toward relevant information and away from that which is irrelevant. This mechanism also requires the perceiver to prioritize certain informational variables in the pursuit of accomplishing some action. What follows is a description of some of the potential informational variables that are implicated in service of carrying out an everyday action like reaching for a cup of coffee.

Perceiving Affordances

The successful picking up of a cup of coffee depends on the actor correctly perceiving at least two informational variables specified in the extended global array: (1) the optical structure that specifies the location of the cup and its surrounding surfaces, and (2) the morphological structures of the actor's body (i.e., arm-length). This interaction between an environment-specific variable (the optical structure) and observer-specific variable (arm-length) was detailed by Gibson (1979), who coined the term *affordance*. Put simply, affordances are possibilities for action, or what is furnished by the environment, "either for good or ill" (p. 127). For example, a chair affords comfortable sitting for an actor if its surface is roughly at knee-height; this may not be the case for a toddler for whom the chair may only afford climbing and/or falling. One may even consider the perceptual experience of any given environment to be the sum total of the affordances that exist at the relevant behavioral scale. The consideration of scale is important to note because of the abundance of information contained in energy arrays that extend far beyond what might be useful to the actor. Take, for instance, the differences in how a snake orients toward its prey compared to how a tiger accomplishes the same task. The snake possesses the capability to sample from very fine-grained heat gradients specified in the thermal array, where small changes in the distribution of heat specify the mouse's location relative to the snake. This information, the changes in the distribution of heat, is not relevant to the tiger, because it exists at a scale not relevant to the tiger in the pursuit of its prey (i.e., the tiger does not possess the sensory apparatus necessary to detect such small fluctuations in heat as does the snake in its heat pit organs); the tiger instead samples from the optic, acoustic, and mechanical arrays to assess the location and possibilities for action in intercepting its prey.

Affordances, then, are the primary objects of perception, capturing what is possible given the environment, and what is detectable given the perceiver. Any reaching action depends on at least these two variables (distance and arm-length for reaching the coffee cup). However, objects do not exist within a vacuum. In fact, any resting object (the cup) viewed from any point of observation will be surrounded and sometimes occluded by other surfaces (e.g., tables, the ground, other resting objects). These objects and surfaces structure the ambient light in a way that is unique to that configuration and accordingly, changes in this structure should carry consequences for the perceiver. If the affordance is specified by some relationship of environment-specific variables (light patterns, distance, etc.) to participant-specific variables (arm-length, energetic potential, etc.), then changes to either the environment or to the observer should change that which is perceived—the affordance.

Perceiving Surfaces

To Gibson, the affordances that exist at the scale relevant to human behavior involve objects and other features of the environment that are surrounded or framed by the ground plane or other surfaces. These surfaces not only structure the ambient light in a particular manner, but they also specify features of those surfaces such as distance and slant, which necessarily impact perceiving an affordance like reaching for a coffee cup.

Gibson's *ground theory of spatial perception* (1950) captures these concerns and provides a framework which specifies the relevant features based on the texture of surfaces. Specifically, the ground theory states that (1) the rate of change in the density of surface texture elements specifies the slant of a surface relative to the observer, and (2) the magnitude difference in the density of texture elements between proximal and distal patches of the surface specifies distance relative to the observer. In the case of the coffee cup, this means that the difference in the density of elements on the table surrounding the cup and the density of elements on the table near the observer specifies the distance-to-cup for the observer. This theory suggests that the observer is sampling the optic array from an egocentric point of view outward and has led researchers to consider the mechanisms at work in this process and how these mechanisms might break down.

Texture Gradient Discontinuities

Sinai, Ooi, and He (1998, Exp. 5) tested Gibson's ground theory in a distance perception paradigm where participants judged the distance-to-target on a ground surface which consisted of grass, concrete, or a combination of both. In the latter case, a discontinuity occurs at the point where the two textures meet. Their results demonstrated that participants made accurate estimates of distance in both blind-walking tasks and perceptual matching tasks when estimates were made over the grass-only or concrete-only ground textures. However, when making estimates across the discontinuity in either direction (grass-concrete and vice versa), observers significantly underestimated the distance-to-target. They argue for a *sequential surface integration (SSI) hypothesis* where this effect arises due to an intrinsic bias toward perceiving the surface beyond the discontinuity as being slanted upward and towards the observer, effectively compressing the space beyond the discontinuity, making the target appear closer to the participant than it would in the absence of the discontinuity (Wu, He, & Ooi, 2007). If the individual is indeed sampling the surface texture from an egocentric point of view outward for the purpose of distance perception, then each patch of surface is sampled and integrated by the visual system up until the discontinuity, at which point the visual system must account for a new patterning of texture elements which results in the spatial compression of the task space containing the new texture gradient.

Feria, Braunstein, and Andersen (2003) extended this investigation by testing individuals in a distance perception paradigm using both frontoparallel displays and simulated ground plane displays on a computer screen. In this case, participants made perceptual matches for target objects that rested on a continuous surface of black and white texture elements, or for objects that rested on a surface with a discontinuity between the participant and the target-object. Overall luminance was held constant by balancing the ratio of black-to-white elements on either side of the discontinuity for each experiment, improving upon Sinai et al.'s original paradigm (1998). Despite these modifications and in concordance with Sinai et al.'s findings, Feria et al. found that participants made smaller distance estimates when the discontinuity was present in both the simulated ground plane and frontoparallel display conditions. These results obtained using simulated displays projected to the computer screen suggest that the perceptual effects of discontinuous surface textures may also exist in fully artificial optic arrays, i.e., virtual reality.

Despite making smaller distance estimates in the discontinuous condition compared with those made in the continuous condition, Feria, et al. (2003) noted that observers overestimated the actual distances simulated in the frontoparallel plane, which aligns with several predictions such as the horizontal-vertical illusion (Künnapas, 1955a) and the framing effect (Künnapas, 1955b). In the horizontal-vertical illusion, when presented with an inverted T shape, observers tend to report the vertical extent as being greater than the horizontal extent. In the case of the framing effect, the extent of a line appears to be larger as a function of decreasing frame size, i.e., a line will look longer if it is seated in a small frame when compared to an identical line in a much larger frame. In the frontoparallel experiments, stimuli were presented on a screen which is wider than it is tall, so when judging vertical extents, the two extremes are much closer to the borders of the frame than in the horizontal, possibly resulting in the observed overestimations. This also aligns with a well-established visual illusion known as the Oppel-Kundt illusion (Coren & Girgus, 1978; Robinson, 1972) in which a vertical extent looks longer than a referent when that extent is subdivided. However, they also note that there are studies in which a reverse Oppel-Kundt illusion has been demonstrated (Obonai 1954; Tedford & Gray 1976; Tedford & Murphy 1978). In these cases, the vertical extent appears to be smaller than the referent, a finding which aligns with the observed discontinuity effects (not the general overestimations). In addition to the reverse Oppel-Kundt effect, the bisection effect (which is a constituent effect of the horizontal-vertical illusion) also predicts that a vertical extent will be perceived as being shorter when it is bisected (Finger & Spelt, 1947). While these phenomena provide hypotheses for the mechanisms underlying the discontinuity effect and the observed overestimations, an explanatory framework has not been forthcoming, nor are there any indications that these phenomena will extend into the perception-action cycle.

Both Sinai et. al. (1998) and Feria et al. (2003) concerned perceptions of distance, whereas the proposed work concerns perceptions of object reachability, which implicitly requires the perception of distance. As such, the perception of distance is just one part of the relationship which determines the affordance of reaching for a coffee cup, so it should follow that introducing texture discontinuities into the surface over which a person reaches for a coffee cup will carry consequences for perceiving the affordance of reaching. If the SSI hypothesis holds true, then the coffee cup should look more reachable (i.e., closer) when a texture discontinuity occurs between it and the participant due to the intrinsic bias of perceiving increased slant beyond the discontinuity. Alternatively, the reaching affordance task may be sufficiently different from the metric estimation of distance in that it has intrinsic meaning for the perceiver couched in the service of action, rather than estimating some abstract concept using arbitrary units. If this is the case, then participants may be accurate in their reaching judgments regardless of the presence of a texture discontinuity. A third outcome is also possible, in which participants may see the coffee cup as being more reachable when there is no discontinuity and less reachable when the discontinuity occurs beyond the cup relative to the observer. This outcome is motivated by the framing effect which would predict that the extent from observer to target-object will look shorter if the frame is very large (i.e., the continuous surface) and farther if the discontinuity rests close behind the object, effectively placing it at the top of the "frame" (i.e., task-space). While, this latter prediction might seem unlikely as the discontinuity rests outside of the relevant task space (i.e., the space between the participant and the target-object) and accordingly should have no bearing on the task at hand, Kim, Carello, and Turvey (2016) demonstrated that optical patterns that occur beyond a target object carry perceptual consequences for estimates of size and distance.

Past research has also demonstrated that observers tend to overestimate their reaching capabilities (Rochat & Wraga, 1997; Mark et al., 1997; Carello et al., 1989; Weast & Proffitt, 2018), that is perceptual boundaries for reaching judgments tend to transition from "yes" to "no" at a point where the ratio of stimulus distance to arm-length exceeds the observer's actual capability for reaching. Indeed, pilot testing in a real-world table-top reaching task showed observers' perceptual boundaries occurring at a distance of 110% of observer arm-length. These findings align with Feria et al.'s observed overestimations of the simulated distance interval, and they have the potential to impact the predictions made above. For a summary of the several phenomena, perceptual effects, illusions, and predictions, see Table 1.

Table 1 *Overview of discontinuity effect predictions for reachability for several hypotheses.*

		Surface Type	
		Continuous	*Discontinuous*
	Sequential Surface Integration	Less Reachable	More Reachable
	Framing Effect	More Reachable	Less Reachable
Hypotheses	*Oppel-Kundt Illusion*	More Reachable	Less Reachable
	Horizontal-Vertical Illusion	More Reachable	Less Reachable
	Bisection Effect	Less Reachable	More Reachable

Note: underestimation of distance will result in more reachable objects and overestimation will result in less reachable objects.

Luminance—The Amount and Availability of Information (Light)

For Gibson, the information for vision is in the ambient light (1950; 1966). The amount of projected and scattered light determines the detectability of visual information. In the most extreme cases, the perceiver will have trouble perceiving anything visually when there is a dearth or an abundance of light, but there should exist some range of the amount of ambient light that allows for the detection of relevant information in the optic array that will specify perceptual events (e.g., affordances). A coffee cup may not appear to be reachable under very low lighting conditions, but it may appear to be reachable under high lighting conditions, all other things being equal. As an alternative to manipulating the global amount of light/information by raising or lowering the projected light via a dimming switch, manipulating the spatial distribution of light/information, that is the light reflected and scattered by surfaces surrounding the coffee cup, should help to pinpoint the amount of task relevant information necessary to accomplish the reaching task.

Piloting in the Real World and VR

Motivated by the question, "How will the amount of light structured by a surface (surface luminance) and the patterning of that light (texture continuity) affect affordance judgments? And further, how might these variables differentially affect affordance judgements as a function of real vs. artificial (virtual) optic arrays?" In pilot study 1, participants provided reachability judgments for a ping-pong ball across four surface conditions: (1) all black, (2) mostly black and some white, (3) mostly white and some black, and (4) all white (Figure 1). A discontinuity occurred only in conditions 2 and 3 where the two surface textures meet 50cm away from the participant. The overall luminance was considered to be higher in conditions 3 and 4 due to more white surface texture than black. Results showed that participants saw objects as being less reachable (farther) when a discontinuity was present, but only when luminance was low. In other words, objects look equally reachable when there is a lot of information (high luminance), but when there is little information (low luminance), the presence of a discontinuity results in objects looking less reachable. Taken at face value, this runs counter to the findings of Sinai et al. in that participants made smaller distance estimates when there were no discontinuities.

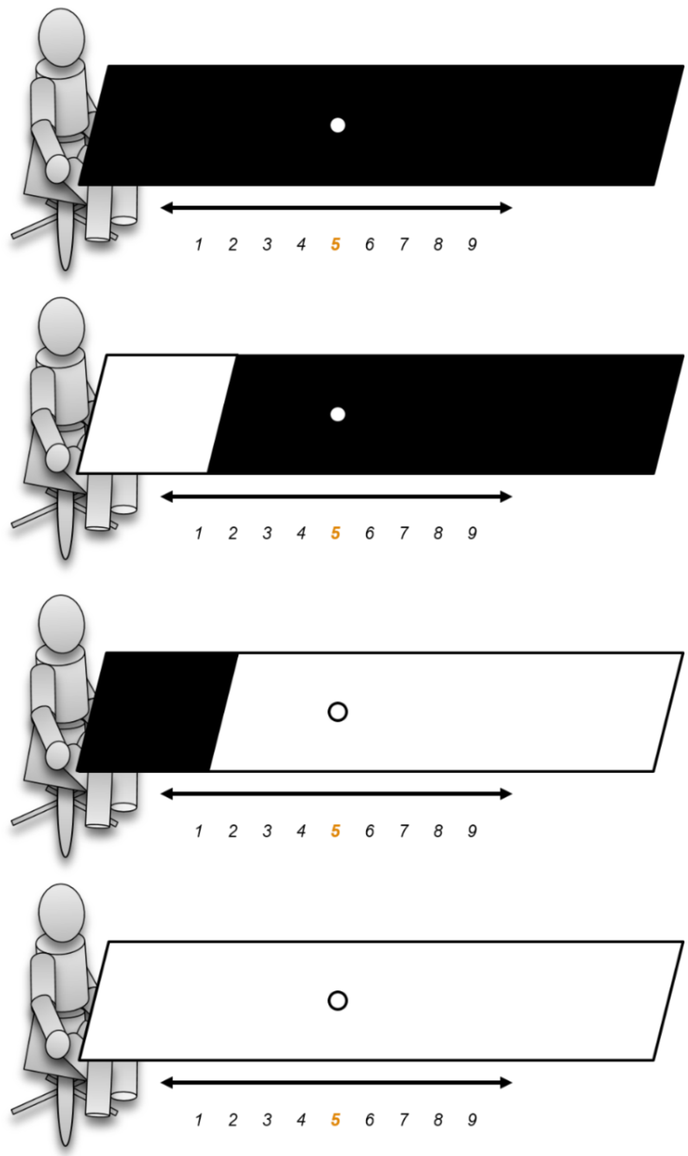

Figure 1. Experimental setup for Pilot 1 and Experiment 1.

Pilot 2 attempted to replicate the findings of Pilot 1 in virtual reality. Abstract virtual objects (cubes and spheres) were used to recreate the table and target-object used in Pilot 1 making sure to preserve the scale of objects. Participants provided reachability judgments for the virtual target-object across the same four (virtual) table top conditions. In this case however, participants tended to see objects as being more reachable in the presence of a discontinuity when compared to the continuous tabletop conditions. In both pilots, participants tended to see objects as being more reachable when luminance was high.

The results from the two pilots seem to contradict each other, with only the second pilot supporting Sinai et al. (1998) and Feria et al. (2003). However, these preliminary findings suggest that both texture discontinuities and surface luminance exert real effects on perception of object-reachability, both in the real world and in virtual reality, and should motivate a more systematic investigation of these variables.

The Current Study

The pilot studies detailed above were inspired by Sinai, Ooi, and He's investigation of perceiving distance across discontinuities (Experiment 5; 1998), where participants underestimated the absolute distance-to-target when viewed across a texture discontinuity along a ground plane. In an effort to realign the investigation with a more ecological approach (Gibson, 1979), we sought to replicate this phenomenon by asking participants to perform a reaching and grasping affordance task which captures the unique environment-actor fit, where the failure or success of the action depends on a participant-specific variable (arm-length) and an environment-specific variable (physical distance-to-target).

The following experiments aimed to extend this investigation beyond the everyday perceptual experience of reaching for objects in the real world by both making improvements to the paradigm used in the pilot and implementing this improved paradigm in an immersive virtual environment (IVE) using the Oculus Rift virtual reality system (https://www.oculus.com/).

A subsidiary aim for these experiments was to highlight the deficiencies in constructing predictive models which assume a static observer and a static environment. In order to construct a model that more closely replicates the dynamics of both observer and environment, movement parameters will be included in the predictive models to account for the contributions of the participants' exploratory patterns to the perceptual outcome, i.e., judging reachability.

CHAPTER II – EXPERIMENT 1

The first experiment aimed to replicate Sinai, Ooi, and He's investigation of distance perception across surface discontinuities (Experiment 5; 1998). Participants made reaching judgements across both continuous and discontinuous surfaces generated through virtual displays in the Oculus Rift head mounted display (HMD). The displays consisted of two virtual objects, a table and a small spherical stimulus (a ping pong ball), both of which were recreated to-scale corresponding to the dimensions of the real table and real stimulus used in Pilot 1. The target object was presented at distances determined by dimensionless π-ratios, which capture each participant's unique fit to the task by comparing some environmental feature with a participant-specific feature (Carello, Grosofsky, Reichel, Solomon, & Turvey, 1989). In this case, the environmental feature is the physical distance-to-target (*d*) relative to the participant, and the participant-specific feature is the length of the participant's arm (*a*):

$$\pi = \frac{d}{a}$$

The resulting ratios specify stimuli that are not reachable if $\pi > 1.00$ and stimuli that are reachable if $\pi \leq 1.00$, where $\pi = 1.00$ corresponds to a stimulus located at the participant's maximal reach. The ecological approach to perception (Gibson, 1979) relies on dimensionless ratios such as these to characterize the participant-task fit by forming a ratio between the environmental and participant-specific constraints. Since these ratios characterize the unique participant-task fit from trial to trial, these ratios provide a better representation of the reaching and grasping affordance than the physical stimulus distance alone.

Participants

A sensitivity power analysis was conducted using the G*Power software package (Version 3.1.9.2; Faul, Erdfelder, Lang, & Buchner, 2007) to determine the size of the effects (d = 0.59) found in the pilot experiment, where n = 14, α = 0.05, and observed power β = 0.80. The current work will aimed to recruit a total of n = 30 participants from the Sona participant pool at the University of Southern Mississippi; these students earned points which were used for course credit in their psychology courses. Collecting a sample of this size allows for the detection of effect sizes on the order of d = 0.37, where α = 0.05, and observed power β = 0.80. All participants were 18 years of age or older and had normal or corrected-to-normal vision. One participant was excluded due to a computational failure resulting in the loss of that participant's data; the final sample size for Experiment 1 was n = 29.

Materials and Apparatus

The apparatus consisted of the consumer version Oculus Rift virtual reality headset and two wireless controllers to be used to record participant responses. The system uses two organic light-emitting diode (OLED) displays (one per eye) which refreshes at a rate of 90Hz. The HMD provides a field of view of 110° and can be tracked in an area of 1.52m × 1.52m using two tabletop motion sensors.

The virtual environments were designed, programmed, and deployed to the HMD using the Unity game engine software (Version 2017.1.1f1), where events and data recording were scripted and coordinated using the C# programming language. The virtual environments mimicked the experimental setup from Pilot 1, where the table and object used were recreated to-scale.

Experimental Design

A 2 (discontinuity: absent/present) × 2 (surface luminance: low/high) × 9 (π-ratio) repeated-measures design was used to probe for any effects or interactions between surface texture discontinuities, overall surface luminance, and physical distance on judgments of reachability for an object sized like a ping-pong ball (3.81cm), where reachability refers to the participant's ability to both reach and grasp the object with the thumb and forefinger without significant postural adjustments. The object's location relative to the observer was set according to π-ratios ranging from 0.6 to 1.4 distance to arm-length. These locations were randomized across four discontinuity-luminance configurations where the table's surface was (1) all black, (2) mostly black, (3) mostly white, or (4) all white (Figure 1). Configurations 1 and 2 were grouped together to create the low-luminance condition and configurations 3 and 4 were grouped together to create the high-luminance condition. Because configurations 2 and 3 were composed of two distinct textures (black and white), a discontinuity naturally occurs at the point where these two textures share a boundary creating the discontinuity-present condition; configurations 1 and 4 then created the discontinuity-absent condition. For consistency with the Pilot 1, the discontinuity always occurred 50cm away from the observer[2].

Procedure

Participants were given verbal explanation of their rights along with a request for informed consent. The experimenter first collected participant-specific measurements such as arm-length (measured from the right inner arm-chest joint to the tip of the thumb), seated eye-height (a non-adjustable chair will be used for all participants), and seated shoulder-height[3]. The experimenter then gave detailed verbal instructions on how to wear and operate the HMD and response controllers.

Perceptual Task

Participants provided yes/no judgments about the reachability of the target object by pressing the corresponding buttons on one of the wireless controllers. Trials consisted of each π-ratio being randomly presented in each table top condition grouped into 3 separate blocks, resulting in 108 total trials. Each block began with a button press, after which trials proceeded automatically with a randomized virtual environment being presented until the participant's response, then the next trial beginning after a 1500ms interstimulus interval (ISI) where the participant will see only an empty, grey environment. Response times, defined by the onset of the trial until the participant's button press, were measured in milliseconds for each trial. Participants also completed 30 practice trials before the experimental session begins so that they had a chance to adjust to the HMD and become familiarized with the response controllers. These trials will be randomized, however only three π-ratios (0.75, 1.05, and 1.35) were used for this practice session.

Participants' head movements were not be physically restricted during the trials, contrary to the pilot study in which head position was fixed using a chin rest. In the present experiment participants were still be limited in their exploratory movements, but only in the virtual space. That is, the participant's body will be unrestricted, but the software running the VR program will restrict the participant's point of view to a fixed point in virtual space, which will be set to correspond with the participant's actual seated eye-height. They will still have 360° range of movement around this fixed point, i.e. the participant can still look upward, downward, and laterally. Soft ambient noise was fed into headphones, which are integrated with the HMD, as a means to reduce auditory stimulation from the real-world lab setting. Once all trials were completed, the participant removed the HMD and was given the opportunity to ask questions about the experiment and hypotheses, after which he or she was granted credit for participation and the session concluded. Experimental sessions did not exceed 30 minutes in length.

The results were expected to conform to two hypotheses where (1) perceptual boundaries (the point at which a judgment transitions from "yes" to "no") will occur at larger π-ratios under high luminance and continuous surface texture conditions, and (2) responses will be fastest at both small and large π-ratios and longest at π-ratios near the perceptual boundary. This latter hypothesis is motivated by the critical slowing down phenomenon described by dynamical systems theory which states that actors will perform slowest at or near the perceived action boundary (Kelso, 1997) due to a natural uncertainty that manifests near transitions between action modes. If the surface-integration hypothesis is true, and participants indeed sample the environment from an egocentric point of view outward, then perceptual boundaries should occur near or beyond a π-ratio of 1.0, the maximum distance that is still considered reachable. The bisection effect will predict similar results if the target object appears more reachable across the discontinuity compared to objects resting on a continuous surface. If this hypothesis does not hold, then it may be the case that objects appear less reachable across the discontinuity due to effects similar to the horizontal-vertical illusion or the Oppel-Kundt illusion. As in pilot study 1, the discontinuity will be at a fixed distance of 50cm and will almost always occur between the observer and the target object. The framing-effect hypothesis does not provide a clear prediction due to the frame of reference (the far edge of the table) occurring after the discontinuity. In a typical demonstration of the framing effect (Kunnapas, 1955b) the line placed inside a frame is usually centered so that both ends are at an equal distance from the frame's edges. In the present experiment the discontinuity and the table's edge can both serve as local frames depending on how close we place the target object from each frame. Experiment 2 aimed to provide a more careful examination of the discontinuity location relative to the target-object

Results

Hierarchical Modeling of Probability and Response Time Data

To predict affordance judgments, hierarchical linear mixed effects logistic regression models were constructed using the *lme4* package (Bates, Maechler, Bolker, & Walker, 2014) in the R environment for statistical computing (R Core Team, 2017). π-ratios, texture discontinuity, and surface luminance were used as fixed factors accounting for any systematic effects introduced by these variables, while trial number (or repetition/block number) and participant ID were used as random factors accounting for potential practice effects or individual differences across participants. To predict response times, hierarchical generalized linear models were constructed using the same package in the R environment. The same factors were included in the models to account for both fixed and random effects that might occur.

Multifractal Analysis of Movement and Response Time Data

While the outcomes of interest are primarily the affordance judgment and the response time, there are other behavioral outcomes that are specific to the manner in which the participant explores the ambient stimulus arrays. Specifically, movement has been shown to modulate perceptual responses through the complex structuring of postural sway (Hajnal, Clark, Doyon, & Kelty-Stephen, 2018). Movements such as postural sway are responsible for directing the flow of optical information and, in turn, defining the manner of exploration and sampling of the environment. Such movements can be recorded as time series data through optical motion tracking systems (e.g., VICON) or by measuring the differences in pixel intensities of adjacent frames in a video (Paxton & Dale, 2013). Motion time series data were recorded using the video differencing method, which will then was processed using a multifractal detrended fluctuation analysis (MF-DFA; Chhabra & Jensen, 1989). This analysis, to be carried out in MATLAB, provides a direct estimation of the multifractal spectrum width (MFW), which is a description of the complexity of a signal, rather than the standard variability, which may be appropriate for use in these endeavors (Kelty-Stephen, 2017).

Head Movement Data

Video recordings of the visual feed shown in the head mounted display were recorded using Open Broadcast Software (OBS; https://obsproject.com/). Recording began at the beginning of each experimental session and ended at the conclusion of the experiment. Videos recorded in mp4 format, then videos were trimmed using FFmpeg (https://ffmpeg.org/) to exclude the practice trials at the beginning of the session and any excess recording beyond the conclusion of the experiment. The resulting videos then spanned only the relevant experimental trials, approximately 8-10 minutes (28,800-36,000 total frames, recorded at 60 frames per second).

Video Differencing

These videos were then processed in MATLAB (https://www.mathworks.com/) using a differencing algorithm adapted from Paxton & Dale (2013) which compares each pixel intensity value (0-255) of each frame to the intensity value occupying the same pixel on the next frame. This method has been used with a static camera to track the motions of interlocuters for the analysis of interpersonal synchrony. In this context, any change in pixel intensity indicates either an object moving, or the observer's head moving, or both, through those pixel locations across frames. In the current context, because head movements direct optic flow in the head mounted display, differences in these intensity values are directly reflective of participant head motion. By averaging these difference values across frames, a timeseries of head displacement magnitudes is generated (approximately 30,000 data points).

Multifractal Analysis

These timeseries (each spanning one participant's entire session) were then processed again in MATLAB using a multifractal detrended fluctuation analysis (MF-DFA) adapted from Chhabra and Jensen's (1989) method of directly estimating the multifractal spectrum width (MFW). This analysis assesses the heterogeneity of variability across all possible scales of the timeseries and characterizes the degree to which large and small fluctuations in the data contribute to the observed variability. The resulting parameter MFW is then considered to be a description of the heterogeneity of power-law relationships in the timeseries, which captures the multiscale interactions in the biological system. The MFW can be thought of as a distant cousin to the traditional standard deviation in that it describes the variability in the data. However, a better characterization of the MFW is as a description of the complexity in the signal, rather than raw variability. Accordingly, the signal might be highly variable, but not very complex, or it may be highly complex, but not very variable. Smaller values of MFW (narrow width) indicate lower complexity, while higher values of MFW (broad width) indicate higher complexity.

Statistical Modeling

Several hierarchical mixed effects linear models were constructed to predict participants' affordance responses (binary, "yes/no") and response times (ms). In each experiment, a "static" model was first constructed to account only for the effects of the environmental variables (distance, discontinuity, and luminance). A second, richer "dynamic" model was then constructed to account for the dynamic properties of the task that emerge from participant-generated head motion. The static model was embedded within the dynamic model (i.e., the dynamic model contained the same set of fixed factors as in the static model, with the addition of the movement parameters). This embedded structure allows for the comparison between the static and dynamic models using a chi-square test which determines if the richer model explains a significant amount of variability above and beyond the simpler model. Reported below are the model comparisons and the results of the richer, dynamic models.

Probability Data. Two generalized mixed effects logistic regression models were constructed to predict participants' affordance responses. The static model was composed of π, Discontinuity, and Luminance as fixed factors, while Block a random factor embedded within Participant to allow the slopes attributable to practice effects and individual differences to vary randomly:

$$Affordance \sim (Block|Participant) + Block + \pi * Discontinutiy * Luminance$$

The dynamic model was composed of the same elements of the static model (i.e., the static was embedded within the dynamic), with the addition of two movement parameters yielded by the differencing and MF-DFA algorithms, mean magnitude head movement and MFW as descriptor of the complexity of head movement. The standard deviation of movement (STD) was excluded from the analysis due to its high correlation with the mean, R^2 = 0.70:

$$Affordance \sim (Block|Participant) + Block + \pi * Discontinuity * Luminance * Mean + \pi * Discontinuity * Luminance * MFW$$

Comparison between these models was significant, $X^2(16, N = 29) = 32.60$, $p = 0.008$, indicating that the dynamic model was able to explain a significant amount of variability above and beyond the static model (Table 2).

Table 2 *Static vs. dynamic models of affordance judgments comparisons for all experiments.*

Experiment	X^2	df	*p*	
1	32.60	16	0.008	**
2	24.84	20	0.208	
3	22.34	20	0.322	
4	96.16	60	0.002	**

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

There was a significant negative main effect of π (β = -20.89, SE = 7.29, p = 0.004), indicating that participant judgments transitioned from "yes" to "no" (coded as 1 and 0, respectively) as π increased (Table 3). There was also a significant negative main effect of Discontinuity (β = -21.85, SE = 11.10, p = 0.049), indicating that "no" judgments were more likely when a discontinuity was present (coded as 1) as opposed to absent (coded as 0). The main effects of Luminance, Mean, and MFW were not significant.

Table 3 *Best fitting mixed effects logistic regression model of affordance judgments in Experiment 1.*

Predictor	β	*SE*	*p*	
Intercept	22.91	9.06	0.011	*
Block	0.13	0.19	0.497	
π	-20.89	7.29	0.004	**
Discontinuity (Present)	-21.85	11.10	0.049	*
Luminance (High)	-5.00	11.88	0.674	
π × Discontinuity (Present)	18.92	9.23	0.040	*
π × Luminance (High)	4.98	9.96	0.617	
Discontinuity (Present) × Luminance (High)	10.07	15.92	0.527	
π × Discontinuity (Present) × Luminance (High)	-9.25	13.29	0.486	
Effects of Mean and its interaction with other terms				
Mean	168.46	146.58	0.250	
π × Mean	-119.18	119.53	0.319	
Discontinuity (Present) × Mean	230.98	179.98	0.199	
Luminance (High) × Mean	217.13	198.52	0.274	
π × Discontinuity (Present) × Mean	-201.26	150.85	0.182	
π × Luminance (High) × Mean	-194.83	167.42	0.245	
Discontinuity (Present) × Luminance (High) × Mean	-276.09	262.43	0.293	
π × Discontinuity (Present) × Luminance (High) × Mean	234.20	220.95	0.289	
Effects of MFW and its interaction with other terms				
MFW	-5.12	4.22	0.225	
π × MFW	4.93	3.34	0.140	
Discontinuity (Present) × MFW	12.53	5.81	0.031	*

Luminance (High) × MFW	0.31	5.38	0.954	
π × Discontinuity (Present) × MFW	-10.95	4.89	0.025	*
π × Luminance (High) × MFW	-0.98	4.58	0.831	
Discontinuity (Present) × Luminance (High) × MFW	-3.46	8.15	0.671	
π × Discontinuity (Present) × Luminance (High) × MFW	234.20	220.95	0.289	

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

There was a significant positive interaction between π and Discontinuity (β = 18.92, SE = 9.23, p = 0.040), indicating that as π increases, participants are more likely to say yes when a discontinuity is present. There was a significant positive interaction between Discontinuity and MFW (β = 12.53, SE = 5.81, p = 0.031), indicating that as the complexity of participant movements increases, the likelihood of responding "yes" increases when discontinuity is present. There was a significant negative interaction between π, Discontinuity, and MFW (β = -10.95, SE = 4.89, p = 0.025), indicating that the differences between discontinuity conditions in terms of participant responses decrease with increasing values of π and MFW. No other interactions were significant.

Response Time Data. Response latencies tend to be highly skewed (Fazio, 1990) and methods such as logarithmic or z-score transformations are common. However, rather than transform the data in this case, trials in which the response time exceeded two standard deviations above the mean were excluded. In all four experiments, this method resulted in loss of approximately 4% of the data. Average response time was 1,630ms (SD = 1,689ms), resulting in a cutoff value of 5,007ms.

Two linear mixed effects regression models were constructed to predict participants' response times. Again, the static model was composed of Block, π, Discontinuity, and Luminance as fixed factors, while Block was embedded within Participant to allow the slopes attributable to practice effects and individual differences to vary randomly:

$$Response\ Time \sim (Block|Participant) + \pi * Discontinuity * Luminance$$

The dynamic model was again composed of the same elements of the static model (i.e., the static was embedded within the dynamic), with the addition of two movement parameters yielded by the differencing and MF-DFA algorithms, mean magnitude head movement and MFW as descriptor of the complexity of head movement:

$$Response\ Time \sim (Block|Participant) + \pi * Discontinuity * Luminance * Mean \\ + \pi * Discontinuity * Luminance * MFW$$

The comparison between these models was not significant, but trending, $X^2(16, N = 29) = 23.69$, p = 0.097, indicating that the dynamic model did not explain a significant amount of variability above and beyond the static model (Table 4).

Table 4 *Static vs. dynamic models of response times comparisons for all experiments.*

Experiment	Likelihood Ratio	df	*p*	
1	23.69	16	0.097	.
2	44.06	20	0.002	**
3	15.60	20	0.741	
4	75.64	60	0.084	.

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1

There were no significant main effects or interactions between these variables when predicting response times (Table 5). However, there were marginal positive interactions between π and Mean (β = 14.33, SE = 7.56, p = 0.058), and also π and MFW (β = 0.50, SE = 0.28, p = 0.081).

Table 5 *Best fitting mixed effects linear regression model of response times in Experiment 1.*

Predictor	*β*	*SE*	*p*	
Intercept	1.15	0.59	0.049	*
π	-0.17	0.51	0.734	
Discontinuity (Present)	-0.45	0.75	0.550	
Luminance (High)	-0.94	0.74	0.205	
π × Discontinuity (Present)	0.65	0.73	0.374	
π × Luminance (High)	1.02	0.73	0.162	
Discontinuity (Present) × Luminance (High)	1.36	1.05	0.198	
π × Discontinuity (Present) × Luminance (High)	-1.22	1.03	0.233	
Effects of Mean and its interaction with other terms				
Mean	-4.44	8.60	0.610	
π × Mean	14.33	7.56	0.058	.
Discontinuity (Present) × Mean	11.62	10.92	0.287	
Luminance (High) × Mean	9.57	10.91	0.380	
π × Discontinuity (Present) × Mean	-15.78	10.69	0.140	
π × Luminance (High) × Mean	-11.41	10.67	0.285	
Discontinuity (Present) × Luminance (High) × Mean	-25.36	15.42	0.100	
π × Discontinuity (Present) × Luminance (High) × Mean	24.50	15.06	0.104	
Effects of MFW and its interaction with other terms				
MFW	-0.56	0.33	0.101	
π × MFW	0.50	0.28	0.081	.
Discontinuity (Present) × MFW	-0.01	0.41	0.983	
Luminance (High) × MFW	0.52	0.41	0.211	

π × Discontinuity (Present) × MFW	-0.09	0.40	0.831
π × Luminance (High) × MFW	-0.51	0.40	0.206
Discontinuity (Present) × Luminance (High) × MFW	-0.30	0.59	0.610
π × Discontinuity (Present) × Luminance (High) × MFW	0.20	0.57	0.720

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

CHAPTER III - EXPERIMENT 2

The second experiment aimed to investigate discontinuity alone while keeping overall surface luminance constant as was done in Feria, et al. (2003). The goal was to further test the surface-integration hypothesis in the reaching affordance task in VR by controlling the amount of visual information (light) and manipulating only the patterning of the information by placing the discontinuity at several different locations.

Participants

The same power analysis used in Experiment 1 was used to determine the sample size needed, $n = 30$. Participants were again recruited from the Sona participant pool at the University of Southern Mississippi, and participants were again awarded points to be used for course credit in their psychology courses. One participant was excluded due to a computational failure resulting in the loss of that participant's data; the final sample size for Experiment 1 was $n = 29$.

Materials and Apparatus

The apparatus was the same one used in Experiment 1, the Oculus Rift VR headset with its two wireless controllers. The virtual environments and stimuli were generated using the same computational tools and methods used in Experiment 1.

Experimental Design

A 5 (discontinuity location) × 9 (π-ratio) repeated measures design was used to investigate the effects of a texture discontinuity and its location relative to the observer and the target object where the discontinuity occurred at one of five locations: 0%, 20%, 40%, 60%, or 80% of the surface's length, relative to the observer (Figure 2). In Experiment 1, the discontinuity occurred at the boundary of two distinct surface textures which varied in total surface area, one colored black and one colored white. As a consequence, the overall surface luminance varied as a function of the ratio of black to white surface texture, where more white surface would result in higher overall surface luminance and more black space would result in lower overall surface luminance. To control for potential changes to the surface luminance from trial to trial, the surface textures on either side of the discontinuity were a single neutral gray color (pixel intensity value of 127.5) with a thin black line acting as the texture discontinuity. The π-ratios were the same as those used in Experiment 1.

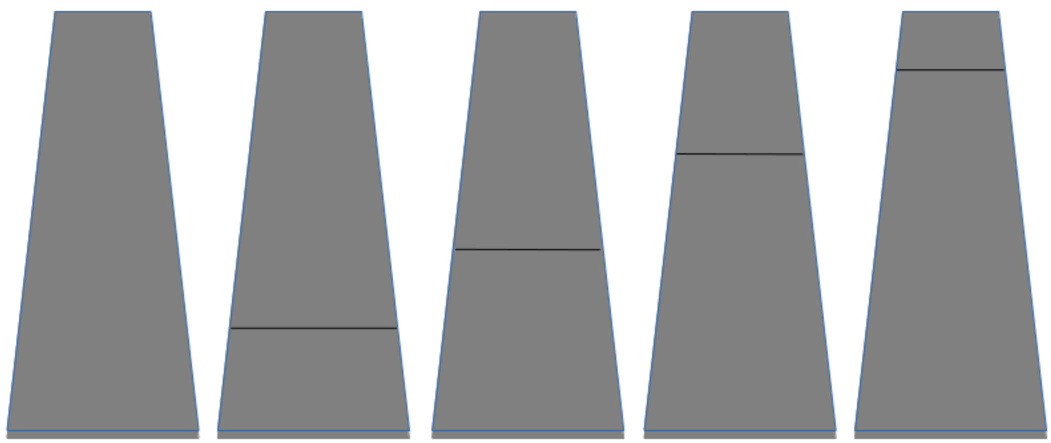

Figure 2. Discontinuity conditions in Experiment 2.

Procedure

The procedure was the same as the one used in Experiment 1. Participants again provided yes/no judgments about the reachability of the target object by pressing the corresponding buttons on the wireless controllers. Trials were grouped into 45 randomized trials with repetitions across three blocks, resulting in 135 total trials. The trial sequence was the same as the self-paced trial sequence used in Experiment 1 preceded by 30 practice trials using the same three π-ratios.

The results of Experiment 2 were expected to further clarify the possibility of participants underestimating distances across the discontinuity or the possibility of participants perceiving a compressed task space resulting in perceptual boundaries being pushed toward or away from the observer depending on the object's location within the frame of reference (the table). Specifically, two hypotheses were tested: (1) perceptual boundaries will occur at π-ratios less than 1.0 when the discontinuity occurs between the observer and the target object and at π-ratios greater than 1.0 when the discontinuity occurs beyond the target object, and (2) responses will be fastest at both small and large π-ratios and slowest at π-ratios near the perceptual boundary. If the SSI hypothesis holds true, then participants should have judged objects as more reachable when the discontinuity occurs between the point of observation and the target object. Further, the SSI makes no claims of the influence of optical information that resides outside of the relevant task-space on task-relevant judgments (e.g., Kim et al., 2017), as discontinuities beyond the target object should not affect in accurate perception. The bisection effect should predict results similar to those of the SSI. However, if the framing effect is true, then the target object should appear to be more reachable when there are no discontinuities present (i.e., the object has the largest frame of reference possible, causing the participant to underestimate the target distance), and less reachable when the discontinuity is present, particularly when the discontinuity is both near and behind the object (i.e., the object is at the upper edge of the reference frame). As in Experiment 1, uncertainties still remain in what the framing effect should predict when the discontinuity occurs between the participant and the target object. The bisection effect should again align with the SSI hypothesis predictions, including the discounting of potential effects of discontinuities that occur beyond the target object (i.e., the depth-interval is not bisected by the discontinuity). Similarly, the Oppel-Kundt illusion hypothesis should only predict effects where the discontinuity occurs between the participant and the object, resulting in overestimated depth-intervals and less reachable objects. The horizontal-vertical illusion might predict two different effects of discontinuity depending on the location of the discontinuity. If the discontinuity occurs beyond the object, then the perceived depth-interval of the object-to-discontinuity might be exaggerated, resulting in the object appearing to be closer and more reachable. Alternatively, if the discontinuity occurs between the participant and the object, then the perceived depth-interval of discontinuity-to-object might be exaggerated, resulting in the object appearing to be farther and less reachable. These two predictions assume that the perceived location of the nearer visual landmark (object and discontinuity, respectively) remains fixed, and that the exaggeration "pushes" the more distant visual landmark even further away from the observer.

Results

Probability Data

Two generalized mixed effects logistic regression models were constructed to predict participants' affordance responses. The static model was composed of Block, π, and Discontinuity as fixed factors, while Block was embedded within Participant as a random factor (Note: Discontinuity was specified as a factor variable in both models to include comparisons for all levels against the control stimulus in which no discontinuity is present):

$$Affordance \sim (Block|Participant) + Block + \pi * Discontinutiy$$

The dynamic model was composed of the same elements of the static model (i.e., the static was embedded within the dynamic), again with the addition of mean magnitude head movement and MFW. STD was excluded from the analysis due to its high correlation with the mean, $R^2 = 0.88$:

$$Affordance \sim (Block|Participant) + Block + \pi * Discontinuity * Mean + \pi * Discontinuity * MFW$$

The comparison between these models was not significant, $X^2(20, N = 29) = 24.84$, $p = 0.208$, indicating that the dynamic model did not explain a significant amount of variability above and beyond the static model (Table 2).

There was a significant negative main effect of π ($\beta = -18.35$, SE = 2.48, $p < 0.001$), indicating that participant judgments transition from “yes” to “no” as π increased (Table 6). There was also a significant positive main effect of Mean ($\beta = 59.10$, SE = 22.28, $p = 0.008$), indicating that the likelihood of responding “yes” increased as magnitude head movement increased. There was a significant negative main effect of MFW ($\beta = -6.09$, SE = 2.56, $p = 0.017$), indicating that the likelihood of responding “yes” decreased as complexity of movement increased. The main effects of the Discontinuity positions at 20, 40, 60, and 80% of the table’s length compared to 0% (the intercept) were not significant.

Table 6 *Best fitting mixed effects logistic regression model of affordance judgments in Experiment 2.*

Predictor	*β*	*SE*	*p*	
Intercept	21.61	3.14	< 0.001	***
Block	-0.19	0.21	0.358	
π	-18.35	2.48	< 0.001	***
Discontinuity (20%)	-2.00	3.85	0.604	
Discontinuity (40%)	-5.31	3.59	0.139	
Discontinuity (60%)	4.66	4.07	0.252	
Discontinuity (80%)	-4.54	3.57	0.204	
π × Discontinuity (20%)	1.36	3.34	0.684	
π × Discontinuity (40%)	4.18	3.02	0.166	
π × Discontinuity (60%)	-4.11	3.43	0.230	
π × Discontinuity (80%)	3.68	3.04	0.226	
Effects of Mean and its interaction with other terms				
Mean	59.10	22.28	0.008	**
π × Mean	-33.99	16.92	0.045	*
Discontinuity (20%) × Mean	-0.61	22.67	0.979	
Discontinuity (40%) × Mean	-1.16	25.55	0.964	
Discontinuity (60%) × Mean	-30.68	23.74	0.196	
Discontinuity (80%) × Mean	12.46	22.71	0.583	
π × Discontinuity (20%) × Mean	-3.94	19.67	0.841	
π × Discontinuity (40%) × Mean	9.25	21.17	0.662	
π × Discontinuity (60%) × Mean	31.05	19.74	0.116	
π × Discontinuity (80%) × Mean	-5.43	19.22	0.778	
Effects of MFW and its interaction with other terms				
MFW	-6.09	2.56	0.017	*
π × MFW	4.18	2.13	0.050	*
Discontinuity (20%) × MFW	1.44	3.25	0.659	
Discontinuity (40%) × MFW	4.22	2.95	0.153	
Discontinuity (60%) × MFW	-0.95	3.23	0.769	
Discontinuity (80%) × MFW	2.82	3.01	0.349	
π × Discontinuity (20%) × MFW	-0.72	3.01	0.810	

π × Discontinuity (40%) × MFW	-4.12	2.70	0.128
π × Discontinuity (60%) × MFW	0.10	3.01	0.974
π × Discontinuity (80%) × MFW	-2.74	2.78	0.324

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1

There was a significant negative interaction between π and Mean (β = -33.99, SE = 16.92, p = 0.045), indicating that as π increased, the likelihood of responding "yes" decreased with increases in magnitude head movement. There was also a significant positive interaction between π and MFW (β = 4.18, SE = 2.13, p = 0.050), indicating that as π increased, the likelihood of responding "yes" increased with increases in complexity of movement. No other interactions were significant.

Response Time Data

Again, response times exceeding two standard deviations above the mean were excluded. Average response time was 1,700ms (SD = 1,899ms), resulting in a cutoff value of 5,499ms. Two linear mixed effects regression models were constructed to predict participants' response times. The static model was composed of Block, π, and Discontinuity as fixed factors, while Block was embedded within Participant as a random effect:

$$Response\ Time \sim (Block|Participant) + \pi * Discontinuity$$

The dynamic model was composed of the same elements of the static model (i.e., the static was embedded within the dynamic), with the addition of mean magnitude head movement and MFW:

$$Response\ Time \sim (Block|Participant) + \pi * Discontinuity * Mean + \pi * Discontinuity * MFW$$

The comparison between these models was significant, $X^2(20, N = 29) = 44.06$, p = 0.002, indicating that the dynamic model explained a significant amount of variability above and beyond the static model (Table 3).

There was a significant positive main effect of π (β = 1.46, SE = 0.37, $p < 0.001$), indicating that response time increased with increases in π (Table 7). There was also a significant negative interaction between π and MFW (β = -0.77, SE = 0.30, $p = 0.011$), indicating that as distance increased, response times decreased with increases in complexity of movement. No other effects or interactions were significant.

Table 7 *Best fitting mixed effects linear regression model of response times in Experiment 2.*

Predictor	*β*	*SE*	*p*	
Intercept	-0.06	0.43	0.898	
π	1.46	0.37	< 0.001	***
Discontinuity (20%)	0.30	0.55	0.585	
Discontinuity (40%)	0.44	0.52	0.401	
Discontinuity (60%)	0.31	0.53	0.561	
Discontinuity (80%)	0.18	0.53	0.740	
π × Discontinuity (20%)	-0.49	0.55	0.373	
π × Discontinuity (40%)	-0.68	0.51	0.178	
π × Discontinuity (60%)	-0.56	0.53	0.292	
π × Discontinuity (80%)	-0.48	0.52	0.360	
Effects of Mean and its interaction with other terms				
Mean	-1.00	4.61	0.830	
π × Mean	4.66	4.02	0.246	

Discontinuity (20%) × Mean	-0.63	5.91	0.915	
Discontinuity (40%) × Mean	-5.00	5.63	0.375	
Discontinuity (60%) × Mean	1.54	5.74	0.789	
Discontinuity (80%) × Mean	2.99	5.72	0.601	
π × Discontinuity (20%) × Mean	2.61	5.97	0.662	
π × Discontinuity (40%) × Mean	7.17	5.48	0.191	
π × Discontinuity (60%) × Mean	1.17	5.71	0.837	
π × Discontinuity (80%) × Mean	-0.92	5.63	0.871	
Effects of MFW and its interaction with other terms				
MFW	0.44	0.36	0.229	
π × MFW	-0.77	0.30	0.011	*
Discontinuity (20%) × MFW	-0.26	0.45	0.569	
Discontinuity (40%) × MFW	-0.01	0.43	0.981	
Discontinuity (60%) × MFW	-0.32	0.44	0.471	
Discontinuity (80%) × MFW	-0.26	0.44	0.553	
π × Discontinuity (20%) × MFW	0.37	0.45	0.410	
π × Discontinuity (40%) × MFW	0.10	0.41	0.805	
π × Discontinuity (60%) × MFW	0.39	0.43	0.361	
π × Discontinuity (80%) × MFW	0.42	0.43	0.326	

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1

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CHAPTER IV – EXPERIMENT 3

The third experiment aimed to investigate the effects of the overall luminance of the surface in the absence of any surface texture discontinuities. In this case, the goal was to further test the hypothesis that the amount of visual information (light) will carry consequences for perceiving the reaching affordance in VR while controlling for surface continuity.

Participants

The same power analysis used in Experiment 1 was used to determine the sample size needed, $n = 30$. Participants will again be recruited from the Sona participant pool at the University of Southern Mississippi, and participants will again be awarded points to be used for course credit in their psychology courses. Two participants were excluded due to a computational failure resulting in the loss of that participant's data; the final sample size for Experiment 1 was $n = 28$.

Materials and Apparatus

Same as in previous experiments.

Experimental Design

A 5 (luminance) × 9 (π-ratio) repeated measures design was used to investigate the effects of the overall surface luminance on the perception of the reaching affordance. Five levels of surface luminance ranging from black to white were used where the surface texture had a greyscale value defined by 8-bit integers ranging from 0 (black) to 255 (white) in equally spaced intensity values, which specify the intensity of each pixel displaying the virtual surface: 0.00, 63.75, 127.50, 191.25, and 255.00 (Figure 3). No texture discontinuities were used in this case and the π-ratios were the same as those used in Experiment 1.

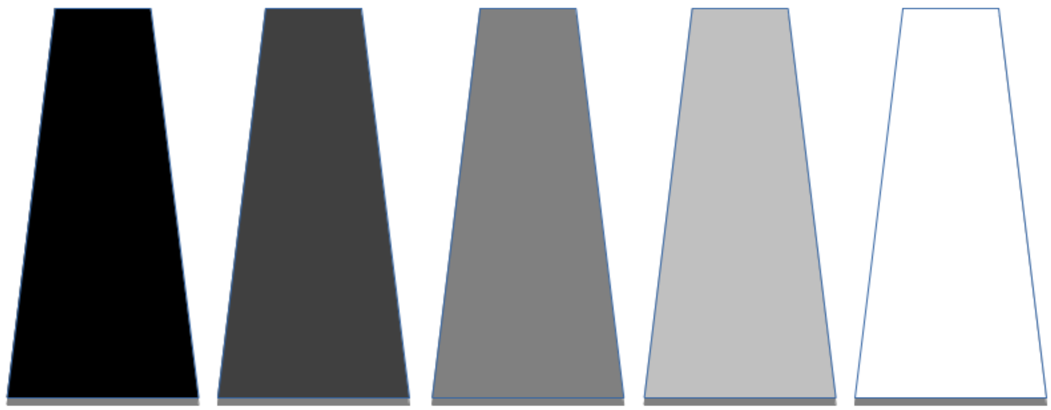

Figure 3. Luminance conditions in Experiment 3.

Procedure

The procedure and measurements were the same as the one used in Experiment 2.

The results of Experiment 3 were expected to further clarify the possibility that the amount of visual information (light) will carry consequences for perceiving the reaching affordance. Specifically, two hypotheses were tested: (1) perceptual boundaries will occur at π-ratios closer to 1.0 as a function of increasing surface luminance, indicating that richer optic arrays allow participants to make more accurate perceptual responses with respect to their action capabilities, while lower surface luminance will result in perceptual boundaries occurring at π-ratios different than 1.0, indicating that perceptual responses that are based on impoverished optic arrays fail to accurately reflect the current environmental task constraints resulting in perceptual errors (e.g. “yes” responses to stimuli at positions where $\pi > 1.0$ or "no" responses to stimuli at positions where $\pi \leq 1.0$), and (2) responses will be fastest at both small and large π-ratios, particularly when luminance is high. The SSI hypothesis suggests that perception tends to rely on intrinsic bias when luminance levels are low, thus predicting underestimation of distance, and as a consequence a perceptual boundary occurring at smaller π values compared to high luminance conditions. Any significant effects in this experiment should support Gibson's theory that the ambient light structured by surfaces in the task-relevant action space should carry consequences for the realization of affordances such as reaching.

Results

Probability Data

Two generalized mixed effects logistic regression models were constructed to predict participants' affordance responses. The static model was composed of Block, π, and Luminance as fixed factors, while Block was embedded within Participant as a random factor (Note: Luminance was specified as a factor variable in both models to include comparisons for all levels against the control stimulus, the black tabletop):

$$Affordance \sim (Block|Participant) + Block + \pi * Luminance$$

The dynamic model was composed of the same elements of the static model (i.e., the static was embedded within the dynamic), again with the addition of mean magnitude head movement and MFW. STD was excluded from the analysis due to its high correlation with the mean, $R^2 = 0.74$:

$$Affordance \sim (Block|Participant) + Block + \pi * Luminance * Mean + \pi * Luminance * MFW$$

The comparison between these models was not significant, $X^2(20, N = 28) = 22.34$, p = 0.322, indicating that the dynamic model did not explain a significant amount of variability above and beyond the static model (Table 2).

There was a significant negative main effect of π (β = -13.66, SE = 2.05, p < 0.001), indicating that the likelihood of responding "yes" decreased with increases in values of π (Table 8). There was a significant negative main effect of Mean (β = -79.52, SE = 9.26, p < 0.001), indicating that the likelihood of responding "yes" decreased as magnitude head movement increased. There was also a significant positive main effect of MFW (β = 14.15, SE = 3.68, p < 0.001). The main effects of Luminance levels 64, 128, 192, and 255 compared to 0 were not significant.

Table 8 *Best fitting mixed effects logistic regression model of affordance judgments in Experiment 3.*

Predictor	β	*SE*	p	
Intercept	16.06	2.72	< 0.001	***
Block	-0.01	0.18	0.977	
π	-13.66	2.05	< 0.001	***
Luminance (64)	-2.77	3.25	0.395	
Luminance (128)	-1.42	3.01	0.638	
Luminance (192)	-2.74	3.06	0.371	
Luminance (255)	-2.80	2.92	0.338	
π × Luminance (64)	2.53	2.80	0.368	
π × Luminance (128)	1.22	2.61	0.640	
π × Luminance (192)	2.73	2.68	0.307	
π × Luminance (255)	2.95	2.51	0.241	
Effects of Mean and its interaction with other terms				
Mean	-79.52	9.26	< 0.001	***

π × Mean	63.46	8.15		< 0.001	***
Luminance (64) × Mean	62.33	10.97		< 0.001	***
Luminance (128) × Mean	92.13	9.46		< 0.001	***
Luminance (192) × Mean	106.90	7.35		< 0.001	***
Luminance (255) × Mean	147.50	8.04		< 0.001	***
π × Luminance (64) × Mean	-57.28	9.38		< 0.001	***
π × Luminance (128) × Mean	-79.10	7.36		< 0.001	***
π × Luminance (192) × Mean	-104.20	6.85		< 0.001	***
π × Luminance (255) × Mean	-138.40	7.03		< 0.001	***
Effects of MFW and its interaction with other terms					
MFW		14.15	3.68	< 0.001	***
π × MFW		-11.83	2.79	< 0.001	***
Luminance (64) × MFW		-1.98	4.22	0.639	
Luminance (128) × MFW		-6.01	3.98	0.131	
Luminance (192) × MFW		-4.96	4.23	0.240	
Luminance (255) × MFW		-8.37	3.77	0.026	*
π × Luminance (64) × MFW		1.57	3.56	0.658	
π × Luminance (128) × MFW		4.61	3.38	0.172	
π × Luminance (192) × MFW		4.03	3.60	0.263	
π × Luminance (255) × MFW		7.00	3.20	0.029	*

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

There were significant positive interactions between the π and the Mean, and also between all levels of luminance and the Mean (see Table 8), indicating that as distance increased, and when luminance was higher relative to zero luminance, the likelihood of responding "yes" increased with higher magnitude head movement. This difference increased gradually as seen by the monotonic increase in the estimates of these interactions. There also were significant negative three-way interactions between π, the Mean, and each level of Luminance (see Table 8), indicating that with increases in distance and head movement, the likelihood of responding “yes” progressively increased with each level of luminance relative to zero luminance.

There was a negative interaction between π and MFW (β = -11.83, SE = 2.79, p < 0.001), indicating that with increasing distance, the likelihood of responding “yes” decreases with increases in movement complexity. There was a significant negative interaction between the highest Luminance level (255) and MFW (β = -8.37, SE = 3.77, p = 0.026) indicating that with increases in complexity of movement, the likelihood of responding “yes” is lower in the highest Luminance condition (255) relative to 0 luminance. There was also a significant positive three-way interaction between π, Luminance (255), and MFW (β = 7.00, SE = 3.20, p = 0.029), indicating that with increasing distance, differences between the two Luminance conditions (0 and 255) get larger as complexity of movement increases with respect to the likelihood of responding “yes”.

Response Time Data

Average response time was 1,594ms (SD = 1,699ms), resulting in a cutoff value of 4,992ms. Two linear mixed effects regression models were constructed to predict participants’ response times. The static model was composed of Block, π, and Luminance as fixed factors, while Block was embedded within Participant as a random factor:

$$Response\ Time \sim (Block|Participant) +\ \pi * Luminance$$

The dynamic model was composed of the same elements of the static model (i.e., the static was embedded within the dynamic), with the addition of mean magnitude head movement and MFW:

$$Response\ Time \sim (Block|Participant) + \pi * Luminance * Mean + \pi * Luminance * MFW$$

The comparison between these models was not significant, $X^2(20, N = 28) = 15.60$, p = 0.741, indicating that the dynamic model did not explain a significant amount of variability above and beyond the static model (Table 3).

There was a significant positive main effect of π ($\beta = 1.45$, SE = 0.37, $p < 0.001$), indicating that response time increased with increases in π (Table 9). There was also a significant negative interaction between π and MFW ($\beta = -0.79$, SE = 0.40, $p = 0.050$), indicating that with increasing distance, the likelihood of responding “yes” decreases with increases in complexity of movement. No other effects or interactions were significant.

Table 9 *Best fitting mixed effects linear regression model of response times in Experiment 3.*

Predictor	*β*	*SE*	*p*	
Intercept	-0.01	0.44	0.990	
π	1.45	0.37	< 0.001	***
Luminance (64)	0.30	0.54	0.578	
Luminance (128)	0.71	0.54	0.188	
Luminance (192)	0.36	0.54	0.509	
Luminance (255)	0.84	0.54	0.119	
π × Luminance (64)	-0.39	0.52	0.461	
π × Luminance (128)	-0.81	0.52	0.120	
π × Luminance (192)	-0.36	0.52	0.492	
π × Luminance (255)	-0.81	0.53	0.126	
Effects of Mean and its interaction with other terms				
Mean	3.82	4.99	0.450	

π × Mean	1.18	4.16	0.776	
Luminance (64) × Mean	-2.79	6.10	0.648	
Luminance (128) × Mean	-0.08	6.07	0.989	
Luminance (192) × Mean	2.45	6.04	0.686	
Luminance (255) × Mean	-0.88	6.09	0.885	
π × Luminance (64) × Mean	2.74	5.93	0.644	
π × Luminance (128) × Mean	0.26	5.91	0.966	
π × Luminance (192) × Mean	-2.46	5.87	0.675	
π × Luminance (255) × Mean	-0.09	5.92	0.988	
Effects of MFW and its interaction with other terms				
MFW	0.31	0.48	0.530	
π × MFW	-0.79	0.40	0.050	*
Luminance (64) × MFW	-0.15	0.58	0.802	
Luminance (128) × MFW	-0.78	0.58	0.180	
Luminance (192) × MFW	-0.32	0.58	0.584	
Luminance (255) × MFW	-0.76	0.58	0.193	
π × Luminance (64) × MFW	0.19	0.57	0.735	
π × Luminance (128) × MFW	0.79	0.57	0.165	
π × Luminance (192) × MFW	0.28	0.57	0.619	
π × Luminance (255) × MFW	0.70	0.57	0.216	

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1

CHAPTER V – EXPERIMENT 4

The fourth experiment aimed to revisit the possible interactions between surface texture discontinuities and overall surface luminance and their effects on perceiving the reaching affordance in VR, as was done in the real-world pilot experiment and Experiment 1. However, design improvements and more carefully considered constraints were implemented to systematically vary both surface continuity and luminance in the same manner as Experiments 2 and 3.

Participants

The same power analysis used in Experiment 1 was used to determine the sample size needed, $n = 30$. Participants were again recruited from the Sona participant pool at the University of Southern Mississippi, and participants were again awarded points to be used for course credit in their psychology courses. One extra participant was included due to a scheduling error in the participant pool, resulting in a final sample size of $n = 31$.

Materials and Apparatus

The apparatus was the same one used in Experiment 1, the Oculus Rift VR headset with its two wireless controllers. The virtual environments and stimuli were generated using the same computational tools and methods used in Experiment 1.

Experimental Design

A 5 (discontinuity location) × 3 (luminance) × 9 (π-ratio) repeated measures design was used to investigate the effects and potential interactions between surface texture discontinuities and overall surface luminance on the perception of the reaching affordance. This experiment used the same five discontinuity locations that were used in Experiment 2 and three out of the five surface luminance levels that were used in

Experiment 3 (0.00, 127.50, and 255.00) to create the virtual environments (Figure 4). The π-ratios were the same as those used in Experiment 1.

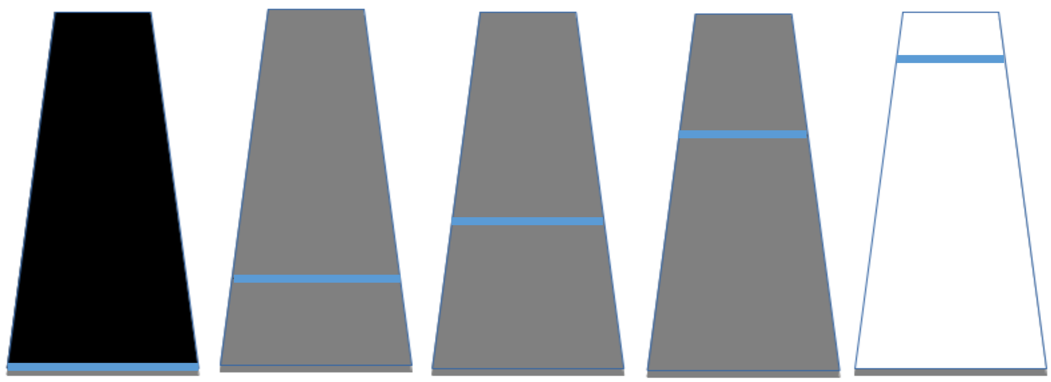

Figure 4. Table surface conditions in Experiment 4.

Note: The color of the discontinuity was changed to blue so that it would still be visible at each luminance level. Some combinations of luminance and discontinuity location omitted for brevity.

Procedure

The procedure was the same as the one used in Experiment 1. Participants again provided yes/no judgments about the reachability of the target object by pressing the corresponding buttons on the wireless controllers. Due to the inclusion of several independent variables, and with the intention to keep experimental session lengths under 30 minutes, trials were only grouped into a single block of 135 trials so that every combination of surface texture, luminance, and π-ratio was experienced only once. The experimental session was still preceded by a block of 30 practice trials using the same three π-ratios used in Experiment 1.

The results of Experiment 4 were expected to provide a more complete explanation of the effects of both the structure and amount of visual information by systematically varying the presence and location of a surface texture discontinuity and the overall surface luminance in an affordance task that requires participants to judge whether an object is within reach. Specifically, three hypotheses were tested: (1) perceptual boundaries will occur at π-ratios closer to 1.0 when luminance is high and the discontinuity occurs between the observer and the target object, (2) the data will reveal an interaction between luminance and discontinuity that mirrors the results of the real-world pilot study 1 where the effects of the discontinuity are attenuated in the presence of richer optic arrays (higher luminance), and (3) responses will be fastest at both small and large π-ratios, particularly when luminance is high and the texture discontinuity occurs beyond the target object. If the surface-integration hypothesis is true, then participants should judge the target object to be more reachable when the discontinuity occurs between it and the observer. However, if the framing-effect hypothesis is true, then participants should judge the object to be more reachable when there is no discontinuity, and less reachable when the discontinuity occurs beyond the object. Predictions for the remaining texture gradient hypotheses should follow those detailed in Experiments 1-3, while allowing for potential interactions with the levels of luminance. However the hypotheses stack up, judgments and response times are expected to be further contextualized by the amount of visual information (light) available at the surface during the judgment. Furthermore, the amount of light should interact with the presence and location of a discontinuity in such a way that mitigates any possible effects on the reaching affordance imposed by a discontinuity, independent of its location. As the results of the pilot studies suggest, the expected results should conform to the notion that when the optic array is richly structured with an abundance of ambient light, little else matters in successfully accomplishing a task such as reaching. However, when there is a dearth of visual information (light), then the visual system must look to other environmental features, such as the continuity of the surface texture, which might be sampled from an egocentric point of view outward as the surface-integration hypothesis suggests, or the action space might appear compressed toward or away from the observer depending on the spatial relationship between the target object and the texture discontinuity.

Results

Probability Data

Two generalized mixed effects logistic regression models were constructed to predict participants' affordance responses. The static model was composed of Block, π, Discontinuity, and Luminance as fixed factors, while Block was embedded within Participant as a random factor (Note: Both Discontinuity and Luminance was specified as factor variables in both models to include comparisons for all levels against the homogeneous tabletop and zero luminance condition, respectively):

$$Affordance \sim (Block|Participant) + Block + \pi * Discontinuity * Luminance$$

The dynamic model was composed of the same elements of the static model (i.e., the static was embedded within the dynamic), again with the addition of mean magnitude head movement and MFW. STD was excluded from the analysis due to its high correlation with the mean, $R^2 = 0.86$:

$$Affordance \sim (Block|Participant) + Block + \pi * Discontinuity * Luminance * Mean + \pi * Discontinuity * Luminance * MFW$$

The comparison between these models was significant, $X^2(60, N = {}^{3}1) = 96.16$, $p = 0.002$, indicating that the dynamic model explained a significant amount of variability above and beyond the static model (Table 2).

While there were some trending effects and interactions involving MFW, or the environmental variables alone, there were no effects or interactions that did not involve the Mean (Table 10). There was a significant positive main effect of Mean ($\beta = 245.91$, SE = 75.59, $p = 0.001$), indicating that the likelihood of responding “yes” increased with higher magnitude movement.

Table 10 *Best fitting mixed effects logistic regression model of affordance judgments in Experiment 4.*

Predictor	*β*	*SE*	*p*	
Intercept	-0.84	945.62	0.999	
Block	11.62	945.60	0.990	
π	-6.96	5.59	0.213	
Discontinuity (20%)	9.29	10.31	0.367	
Discontinuity (40%)	14.60	8.83	0.098	•
Discontinuity (60%)	-8.00	8.56	0.350	
Discontinuity (80%)	3.52	10.30	0.733	
Luminance (128)	9.30	10.21	0.363	
Luminance (255)	5.11	9.65	0.597	
π × Discontinuity (20%)	-8.83	8.75	0.313	
π × Discontinuity (40%)	-14.66	7.72	0.057	•
π × Discontinuity (60%)	6.34	7.48	0.396	
π × Discontinuity (80%)	-5.54	8.85	0.532	
π × Luminance (128)	-9.34	8.73	0.284	
π × Luminance (255)	-5.40	8.29	0.515	
Discontinuity (20%) × Luminance (128)	-6.26	15.70	0.690	
Discontinuity (40%) × Luminance (128)	-12.34	13.42	0.358	

Discontinuity (60%) × Luminance (128)	2.02	13.49	0.881	
Discontinuity (80%) × Luminance (128)	-1.46	15.32	0.924	
Discontinuity (20%) × Luminance (255)	-10.44	14.38	0.468	
Discontinuity (40%) × Luminance (255)	-12.52	13.45	0.352	
Discontinuity (60%) × Luminance (255)	8.60	13.41	0.521	
Discontinuity (80%) × Luminance (255)	-3.68	14.54	0.800	
π × Discontinuity (20%) × Luminance (128)	6.85	13.27	0.606	
π × Discontinuity (40%) × Luminance (128)	12.37	11.61	0.287	
π × Discontinuity (60%) × Luminance (128)	-1.41	11.62	0.903	
π × Discontinuity (80%) × Luminance (128)	4.62	13.06	0.724	
π × Discontinuity (20%) × Luminance (255)	10.75	12.22	0.379	
π × Discontinuity (40%) × Luminance (255)	14.12	11.62	0.224	
π × Discontinuity (60%) × Luminance (255)	-5.16	11.57	0.656	
π × Discontinuity (80%) × Luminance (255)	5.85	12.45	0.639	
Effects of Mean and its interaction with other terms				
Mean	245.91	75.59	0.001	**
π × Mean	-233.89	66.91	0.000	***
Discontinuity (20%) × Mean	-159.68	96.42	0.098	·
Discontinuity (40%) × Mean	-117.30	91.78	0.201	
Discontinuity (60%) × Mean	-77.01	98.49	0.434	
Discontinuity (80%) × Mean	-192.64	97.26	0.048	*
Luminance (128) × Mean	-199.83	90.94	0.028	*
Luminance (255) × Mean	-229.37	85.93	0.008	**
π × Discontinuity (20%) × Mean	151.65	84.97	0.074	·
π × Discontinuity (40%) × Mean	106.00	82.78	0.200	
π × Discontinuity (60%) × Mean	75.41	88.09	0.392	
π × Discontinuity (80%) × Mean	184.12	85.92	0.032	*

π × Luminance (128) × Mean	174.00	81.42	0.033	*
π × Luminance (255) × Mean	196.17	77.30	0.011	*
Discontinuity (20%) × Luminance (128) × Mean	89.21	119.16	0.454	
Discontinuity (40%) × Luminance (128) × Mean	118.70	114.66	0.301	
Discontinuity (60%) × Luminance (128) × Mean	156.56	128.02	0.221	
Discontinuity (80%) × Luminance (128) × Mean	180.32	122.55	0.141	
Discontinuity (20%) × Luminance (255) × Mean	196.39	116.02	0.091	·
Discontinuity (40%) × Luminance (255) × Mean	164.68	114.24	0.149	
Discontinuity (60%) × Luminance (255) × Mean	248.64	131.01	0.058	·
Discontinuity (80%) × Luminance (255) × Mean	163.93	114.04	0.151	
π × Discontinuity (20%) × Luminance (128) × Mean	-86.89	105.51	0.410	
π × Discontinuity (40%) × Luminance (128) × Mean	-105.67	103.68	0.308	
π × Discontinuity (60%) × Luminance (128) × Mean	-141.45	114.58	0.217	
π × Discontinuity (80%) × Luminance (128) × Mean	-166.68	108.65	0.125	
π × Discontinuity (20%) × Luminance (255) × Mean	-167.20	102.63	0.103	
π × Discontinuity (40%) × Luminance (255) × Mean	-141.05	103.35	0.172	
π × Discontinuity (60%) × Luminance (255) × Mean	-229.92	118.19	0.052	·
π × Discontinuity (80%) × Luminance (255) × Mean	-151.53	101.51	0.136	
Effects of MFW and its interaction with other terms				
MFW	-11.40	6.92	0.099	·
π × MFW	8.69	5.75	0.131	
Discontinuity (20%) × MFW	2.50	11.11	0.822	
Discontinuity (40%) × MFW	-10.91	8.78	0.214	
Discontinuity (60%) × MFW	15.73	9.63	0.103	
Discontinuity (80%) × MFW	14.80	12.01	0.218	
Luminance (128) × MFW	5.48	11.22	0.625	
Luminance (255) × MFW	11.75	10.82	0.278	
π × Discontinuity (20%) × MFW	-1.87	9.36	0.842	
π × Discontinuity (40%) × MFW	11.10	7.62	0.145	
π × Discontinuity (60%) × MFW	-14.17	8.35	0.090	·

π × Discontinuity (80%) × MFW	-11.01	10.17	0.279	
π × Luminance (128) × MFW	-3.20	9.48	0.735	
π × Luminance (255) × MFW	-8.96	9.21	0.330	
Discontinuity (20%) × Luminance (128) × MFW	0.55	17.49	0.975	
Discontinuity (40%) × Luminance (128) × MFW	3.81	14.18	0.788	
Discontinuity (60%) × Luminance (128) × MFW	-16.14	15.28	0.291	
Discontinuity (80%) × Luminance (128) × MFW	-16.41	17.49	0.348	
Discontinuity (20%) × Luminance (255) × MFW	-6.12	16.03	0.702	
Discontinuity (40%) × Luminance (255) × MFW	4.22	14.51	0.771	
Discontinuity (60%) × Luminance (255) × MFW	-27.89	15.02	0.063	.
Discontinuity (80%) × Luminance (255) × MFW	-12.61	17.10	0.461	
π × Discontinuity (20%) × Luminance (128) × MFW	-1.58	14.66	0.914	
π × Discontinuity (40%) × Luminance (128) × MFW	-5.05	12.14	0.677	
π × Discontinuity (60%) × Luminance (128) × MFW	14.54	13.02	0.264	
π × Discontinuity (80%) × Luminance (128) × MFW	10.89	14.75	0.460	
π × Discontinuity (20%) × Luminance (255) × MFW	3.08	13.52	0.820	
π × Discontinuity (40%) × Luminance (255) × MFW	-7.47	12.45	0.548	
π × Discontinuity (60%) × Luminance (255) × MFW	22.79	12.87	0.077	.
π × Discontinuity (80%) × Luminance (255) × MFW	8.55	14.47	0.555	

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

There was a significant negative interaction between π and Mean (β = -233.89, SE = 66.91, p < 0.001), indicating that with increases in distance, the likelihood of responding "yes" decreased with increases in magnitude movement. There was a significant negative interaction between the farthest Discontinuity location (80%) and the Mean (β = -192.64, SE = 97.26, p = 0.048), indicating that as magnitude movement increases, the likelihood of responding “yes” is lower in the context of the farthest discontinuity relative to the control stimulus that contains no discontinuity. There was a significant negative interaction between the middle Luminance value (128) and the Mean (β = -199.83, SE = 90.94, p = 0.028), indicating that with increases in magnitude movement, the likelihood of responding “yes” was lower in the context of the middle luminance value relative to zero luminance. There was also a significant negative interaction between the high Luminance value (255) and the Mean (β = -299.37, SE = 85.93, p = 0.008), indicating that with increases in magnitude movement, the likelihood of responding “yes” was lower in the high luminance condition relative to zero luminance.

There was a significant positive three-way interaction between π, Discontinuity (80%), and the Mean (β = 184.12, SE = 85.92, p = 0.032), indicating that with increases in distance, the differences between the farthest discontinuity location and the homogeneous condition increase with higher values of movement magnitude with respect to the likelihood of responding “yes”. There was a significant positive three-way interaction between π, Luminance (128), and the Mean (β = 174.00, SE = 81.42, p = 0.033), indicating that with increases in distance, the differences between the middle luminance value and zero luminance increase with higher values of movement magnitude with respect to the likelihood of responding “yes”. There was a significant positive three-way interaction between π, Luminance (255), and the Mean (β = 196.17, SE = 77.30, p = 0.011), indicating the same pattern with a larger estimate. No other effects or interactions were significant.

Response Time Data

Average response time was 1,403ms (SD = 1,327ms), resulting in a cutoff value of 4,057ms. Two linear mixed effects regression models were constructed to predict participants' response times. The static model was composed of Block, π, Discontinuity, and Luminance as fixed factors, while Block was embedded within Participant as a random factor:

$$Response\ Time \sim (Block|Participant) + \pi * Discontinuity * Luminance$$

The dynamic model was composed of the same elements of the static model (i.e., the static was embedded within the dynamic), with the addition of mean magnitude head movement and MFW:

$$Response\ Time \sim (Block|Participant) + \pi * Discontinuity * Luminance * Mean + \pi * Discontinuity * Luminance * MFW$$

The comparison between these models was not significant, but trending, $X^2(60, N = 28) = 75.64$, p = 0.084, indicating that the dynamic model did not explain a significant amount of variability above and beyond the static model (Table 3).

There were no significant effects or interactions between the variables in predicting response times (Table 11). However, the four-way interaction between π, Discontinuity (60%), Luminance (255), and MFW was trending ($\beta = 2.31$, SE = 1.38, $p = 0.094$).

Table 11 *Best fitting mixed effects linear regression model of response times in Experiment 4.*

Predictor	*β*	*SE*	*p*
Intercept	0.17	0.67	0.801
π	0.78	0.64	0.223
Discontinuity (20%)	0.40	0.91	0.663
Discontinuity (40%)	0.41	0.90	0.651
Discontinuity (60%)	-0.76	0.90	0.401
Discontinuity (80%)	0.77	0.91	0.400
Luminance (128)	0.71	0.91	0.435
Luminance (255)	-0.12	0.90	0.896
π × Discontinuity (20%)	-0.60	0.89	0.499
π × Discontinuity (40%)	-0.53	0.88	0.552
π × Discontinuity (60%)	0.75	0.88	0.397
π × Discontinuity (80%)	-0.90	0.89	0.312
π × Luminance (128)	-0.96	0.89	0.280
π × Luminance (255)	0.18	0.88	0.842
Discontinuity (20%) × Luminance (128)	-0.78	1.28	0.542
Discontinuity (40%) × Luminance (128)	0.37	1.27	0.773
Discontinuity (60%) × Luminance (128)	0.15	1.27	0.907
Discontinuity (80%) × Luminance (128)	-1.57	1.29	0.221
Discontinuity (20%) × Luminance (255)	-0.70	1.27	0.581
Discontinuity (40%) × Luminance (255)	-0.90	1.27	0.480
Discontinuity (60%) × Luminance (255)	0.99	1.27	0.435
Discontinuity (80%) × Luminance (255)	-1.00	1.28	0.435
π × Discontinuity (20%) × Luminance (128)	0.93	1.24	0.457
π × Discontinuity (40%) × Luminance (128)	0.27	1.24	0.830
π × Discontinuity (60%) × Luminance (128)	0.41	1.24	0.738
π × Discontinuity (80%) × Luminance (128)	1.95	1.25	0.119

π × Discontinuity (20%) × Luminance (255)	0.76	1.24	0.538
π × Discontinuity (40%) × Luminance (255)	1.02	1.24	0.409
π × Discontinuity (60%) × Luminance (255)	-1.20	1.24	0.332
π × Discontinuity (80%) × Luminance (255)	0.96	1.25	0.443

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

Effects of Mean and its interaction with other terms

Mean	2.90	4.98	0.565
π × Mean	-1.51	4.67	0.747
Discontinuity (20%) × Mean	-3.96	6.87	0.564
Discontinuity (40%) × Mean	-6.81	6.80	0.317
Discontinuity (60%) × Mean	-5.85	6.83	0.392
Discontinuity (80%) × Mean	4.62	6.91	0.504
Luminance (128) × Mean	1.34	6.84	0.845
Luminance (255) × Mean	-0.48	6.82	0.943
π × Discontinuity (20%) × Mean	4.10	6.68	0.540
π × Discontinuity (40%) × Mean	9.31	6.60	0.159
π × Discontinuity (60%) × Mean	5.67	6.61	0.391
π × Discontinuity (80%) × Mean	-6.13	6.75	0.364
π × Luminance (128) × Mean	2.16	6.67	0.746
π × Luminance (255) × Mean	3.04	6.64	0.647
Discontinuity (20%) × Luminance (128) × Mean	-0.52	9.73	0.957
Discontinuity (40%) × Luminance (128) × Mean	1.75	9.69	0.857
Discontinuity (60%) × Luminance (128) × Mean	3.93	9.69	0.685
Discontinuity (80%) × Luminance (128) × Mean	-0.55	9.73	0.955
Discontinuity (20%) × Luminance (255) × Mean	-2.15	9.69	0.824
Discontinuity (40%) × Luminance (255) × Mean	5.18	9.65	0.591
Discontinuity (60%) × Luminance (255) × Mean	2.02	9.68	0.835
Discontinuity (80%) × Luminance (255) × Mean	-9.18	9.71	0.345
π × Discontinuity (20%) × Luminance (128) × Mean	-0.47	9.50	0.961
π × Discontinuity (40%) × Luminance (128) × Mean	-8.30	9.46	0.381
π × Discontinuity (60%) × Luminance (128) × Mean	-6.68	9.42	0.479

π × Discontinuity (80%) × Luminance (128) × Mean	-1.75	9.49	0.854
π × Discontinuity (20%) × Luminance (255) × Mean	1.24	9.44	0.896
π × Discontinuity (40%) × Luminance (255) × Mean	-8.21	9.39	0.382
π × Discontinuity (60%) × Luminance (255) × Mean	-3.72	9.41	0.692
π × Discontinuity (80%) × Luminance (255) × Mean	9.32	9.48	0.325

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1

Effects of MFW and its interaction with other terms

MFW	0.19	0.74	0.801
π × MFW	0.05	0.70	0.947
Discontinuity (20%) × MFW	-0.15	1.01	0.884
Discontinuity (40%) × MFW	0.29	1.00	0.772
Discontinuity (60%) × MFW	1.56	1.00	0.120
Discontinuity (80%) × MFW	-1.14	1.01	0.260
Luminance (128) × MFW	-0.84	1.01	0.407
Luminance (255) × MFW	0.28	1.00	0.781
π × Discontinuity (20%) × MFW	0.33	0.98	0.735
π × Discontinuity (40%) × MFW	-0.33	0.98	0.734
π × Discontinuity (60%) × MFW	-1.60	0.98	0.101
π × Discontinuity (80%) × MFW	1.30	0.99	0.191
π × Luminance (128) × MFW	0.91	0.99	0.358
π × Luminance (255) × MFW	-0.56	0.98	0.570
Discontinuity (20%) × Luminance (128) × MFW	0.76	1.42	0.595
Discontinuity (40%) × Luminance (128) × MFW	-0.71	1.42	0.616
Discontinuity (60%) × Luminance (128) × MFW	-0.73	1.42	0.608
Discontinuity (80%) × Luminance (128) × MFW	1.79	1.43	0.211
Discontinuity (20%) × Luminance (255) × MFW	1.09	1.42	0.443
Discontinuity (40%) × Luminance (255) × MFW	0.42	1.41	0.767
Discontinuity (60%) × Luminance (255) × MFW	-1.89	1.41	0.183
Discontinuity (80%) × Luminance (255) × MFW	1.90	1.42	0.181
π × Discontinuity (20%) × Luminance (128) × MFW	-0.80	1.39	0.566
π × Discontinuity (40%) × Luminance (128) × MFW	0.37	1.38	0.788

π × Discontinuity (60%) × Luminance (128) × MFW	0.26	1.39	0.854	
π × Discontinuity (80%) × Luminance (128) × MFW	-2.15	1.40	0.125	
π × Discontinuity (20%) × Luminance (255) × MFW	-1.03	1.38	0.455	
π × Discontinuity (40%) × Luminance (255) × MFW	-0.31	1.37	0.819	
π × Discontinuity (60%) × Luminance (255) × MFW	2.31	1.38	0.094	.
π × Discontinuity (80%) × Luminance (255) × MFW	-1.77	1.39	0.203	

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

CHAPTER VI – GENERAL DISCUSSION

This work investigated the roles of three environmental variables specified in the ambient optic array of a virtual environment, and also three related movement variables defined by the participant's unconstrained head movements during exploration in an object-reachability affordance task. The environmental variables—the ratio of object-distance to arm-length (π), the presence or absence of a surface texture discontinuity, and the overall surface luminance of the table on which the object rested—were expected to impact reaching judgments and response times according to our hypotheses (Table 1). The movement variables—mean magnitude head movement, standard deviation of head movement, and the multifractal spectrum width (MFW) of head movement—were expected to modulate the effects of the environmental variables in such a way as to contextualize the perceptual responses in terms of the dynamics of exploration. This approach diverges from the assumptions of traditional statistical modeling where both the environment and the observer are static entities, i.e., the perceptual response is modeled as a snapshot.

A related, but subsidiary aim of this work concerned the shortfalls of statistical modeling which fails to account for the dynamics of the environment and observer involved in everyday perceptual tasks. When a predictive model lacks parameters related to the unfolding dynamics of a perception-action task, such as reaching for an object, this model assumes that perception occurs at a single point in time, as a snapshot, with nothing occurring before or after the judgment. Perception and action, however, do not occur moment-to-moment, as if the actor moves from singular stimulus to singular stimulus making a single judgment at each point. Rather, perception and action are better conceived as the singular embodiment of two interwoven aspects of behavior, acting as a continuous flowing cycle where one does not precede the other—each unfolds in time together, dependent on one another. At the risk of invoking some unmoved mover, perception informs action and action informs perception, with no beginning and no end.

To this end, the researcher must endeavor to more closely model perception according to the dynamics of the system being observed. An important consideration in visual tasks is the nested hierarchy of system components, where each level gives rise to interactions with all other levels, producing important variability that is cast away in the domain of the static modeling of perceptual processes. In the context of the current work, remember that for the visual system, the observer has a set of eyes embedded within a head, which rests atop a body, which itself is embedded within a dynamic, ever-changing environment. Any changes at the level of the eyes will inform subsequent movements of the head, which then informs the body, and so on. Similarly, changes at the level of the environment will inform subsequent movements of the body, head, eyes, etc. For Gibson (1966), the senses are considered integrated perceptual systems whose boundaries do not occur at receptors. Rather, these systems incorporate all components related to achieving some goal-directed behavior. Accordingly, when attempting to model any perceptual process, the researcher must attempt to identify and include any and all variables related to the dynamics of a given task. For the task of reaching for an object resting on a table, rather than assuming a static environment and a static observer, this work attempted to reach beyond environmental variables alone, including parameters related to the average magnitude head movement and the overall complexity of those head movements.

Static vs. Dynamic Modeling

First, a static model was constructed to predict perceptual responses and response times using only the environmental variables as fixed predictors. These models assume both a static observer and a static environment, where the predicted response is the result of a singular moment in time—a snapshot. These models do not take into account the dynamics of a process that unfolds over time at the scale of seconds; rather, the model attempts to reconstruct the process as one that occurs instantaneously, without regard to the moments before a response or the moments after. If the goal of this type of modeling is to computationally reconstruct the perceptual response—a response that arises from the interactivity at multiple spatial and temporal scales—then it should be clear to the reader that this model falls short in its reconstruction of the perceptual process as it occurs in the real world, where the observer and the information are always in flux, moving and shifting in response to the demands of the task unfolding in time.

These shortcomings provided the motivation for constructing dynamic models, which incorporate some of the dynamics of the observer, with the expectation that these dynamic models will more closely resemble the real perceptual process as it unfolds over time, rather than as it exists in a singular moment. Average magnitude head movement (henceforth, the "mean") and the multifractal spectrum width (MFW) were computed for each participant at the scale of the full experimental session. These variables were then included in the model as participant-level variables, with a single value for each participant[4]. While this model should be an improvement above and beyond the static model, it should be noted that this model also falls short in modeling the perceptual process in that the variables included are very coarse descriptions of the experiment-wide dynamics of the observer only. The identification and inclusion of finer grain measurements and environment-related dynamics should improve the model further.

In comparing the static and dynamic models across the four experiments, an interesting pattern of results emerged. For the prediction of affordance responses, only Experiments 1 and 4 showed significant improvements to the model when incorporating the movement parameters. This is likely due to the complexity of each experiment regarding the number of variables being tested. Experiments 2 and 3 sought to test only one environmental variable (discontinuity in Exp. 2 and luminance in Exp. 3), and due to this relative simplicity, the static model was sufficient for predicting the perceptual response. This was not the case for Experiments 1 and 4, where both variables were tested together (conflated in Exp. 1 and systematic in Exp. 4). Due to the relative complexity of these experiments, the dynamic movement variables helped to explain more of the total observed variability.

For the prediction of response times, only the model in Experiment 2 improved upon the original static model. The models in Experiments 1 and 4 did not improve significantly, however the comparison statistics were trending (p's < 0.10); the comparison in Experiment 3 was not significant ($p = 0.74$). In this case, rather than considering the differences across experiments in terms of relative complexity, this pattern of results suggests a fundamental difference between the variables and how they relate to the nature of the movement parameters. The following section considers how the environmental and movement variables differ in terms of their temporality, and how these differences might give rise to the pattern of effects shown in these model comparisons.

Temporal vs. Nontemporal Variables & Effects

The improvements in predicting the affordance response in Experiments 1 and 4, but not in Experiments 2 and 3, suggest that, for this task, the static model is sufficient in simpler scenarios, i.e., when considering just a single environmental variable (Experiments 2 and 3). However, when attempting to model the response as a function of multiple environmental variables (Experiments 3 and 4), the static model is not sufficient and requires some consideration of the observer's dynamics. There may be room for further improvement in these models, where more dynamic variables related to both the environment and the perceiver might be included as predictors, as well as finer grained measures where possible.

In modeling response times, a less clear story begins to unfold. That the dynamic model improved upon the static model in Experiment 2 only raises an interesting question about the nature of the variables: which of these variables and movement parameters can be considered temporal and which can be considered nontemporal? The discussion so far has treated the static model as nontemporal in that it assumes each unique combination of environment- and participant-related variables as a snapshot, a single point in time; the dynamic model, in contrast, is considered temporal in that it assumes that the observer is moving, generating dynamic information through optic flow patterns. What has not been considered thus far, is whether the individual variables share the same temporal/nontemporal divide. For example, consider Experiments 2 and 3, where the critical variables of interest are either the location of a discontinuity or the overall surface luminance. In the former, the observer must visually scan the optical layout for some amount of time before perceiving the location of the discontinuity relative to the other environmental features in the optic array. In the latter, there is little need for scanning the surface to perceive the overall luminance as this is a more global feature, where luminance does not vary as a function of location. The observer gets an immediate perceptual impression of the overall, homogeneous luminance. Accordingly, these variables can be considered temporal, or nontemporal, just as the dynamic and static models, respectively. Further, the movement parameters included in the model can be regarded as either temporal or nontemporal as well. Consider the methods used to compute the mean and the MFW of movement. The mean is a single point estimate which describes only the average magnitude movement of the observer across the entire experiment. MFW describes how variability in the dataset grows (or decays) as a function of increasing or decreasing temporal scale, i.e., from the scale of the entire experiment, down to the scale of individual moments, including every available scale between. Accordingly, these movement parameters can be considered temporal (MFW) and nontemporal (mean), just as both the environmental variables and the models which contain these predictors.

With these considerations in mind, that the dynamic model only improved upon the static model of response times in Experiment 2 makes sense in that the dynamic (temporal) model is predicting discontinuity (temporal). In Experiment 3, the dynamic model (temporal) is attempting to model luminance (nontemporal), and as a result, does not improve upon the static (nontemporal) model. Further, the comparisons of models in Experiments 1 and 4 are trending (*p's* < 0.10), suggesting that it may be temporality of these components driving the models. Experiment 3 was the only case where the only environmental variable was nontemporal (luminance; $p = 0.741$). Experiments 1 and 4, as opposed to Experiments 2 and 3, were more complex situations, likely requiring more exploration (i.e., head movement) accounted for in the dynamic model.

Regarding the Hypotheses

This work originally set out to test for effects of surface texture discontinuities and overall surface luminance on judgments of object reachability in virtual reality. Surface texture discontinuities were expected to replicate the findings of Sinai, et al. (1998) in that objects should appear more reachable (i.e., shorter distance) compared to the homogenous surface texture conditions (see Table 1 for additional hypotheses). Luminance was included with the theoretical motivation that if we are to take light as being the information for vision (Gibson, 1950; 1960), then the amount of light absorbed or reflected about the target object should be meaningful in this perceptual task. That is, a surface with higher luminance should structure more ambient light around the target object, thus providing the observer a richer optic array to sample from during the perceptual task, compared to the lower luminance conditions. The movement parameters were expected to both improve the statistical models and help to characterize the effects of the environmental variables by describing the manner in which the observer explored or sampled the information available in the virtual optic array.

Sinai, et al. (1998) found that distance was underestimated when judged across a texture discontinuity in the ground, suggesting a *sequential surface integration (SSI) hypothesis*, which states that there exists an intrinsic bias toward seeing the distal surface as being slanted toward the perceiver, causing the target to appear closer to the observer. Were this hypothesis to hold true, objects in this reaching task should have appeared more reachable (i.e., shorter distance) when being judged across a texture discontinuity.

However, this was not the case—in Experiment 1, objects were seen as being less reachable when a discontinuity was present. This effect was further characterized by interactions with both π and MFW, indicating that less complexity in movement drives this effect, but disappears at further π-ratios. In Experiment 2, which tested discontinuity alone, no effects of discontinuity were present. In Experiment 4, the discontinuity effect diverges from what was seen in Experiment 1 (and the real world pilot) in that the presence of a discontinuity at 80% of the table's length caused objects to appear more reachable as magnitude head movement increases, at further π-ratios. This finding is perhaps unexpected in that the relevant task space, i.e., the distance between the observer and the target, is not bisected by a discontinuity. Rather, the discontinuity occurs well beyond the presumably relevant spatial extent. However, Kim, Carello, and Turvey (2016) found that the optical structure beyond the relevant task space affected the perceived size of an object. A potential driver of this effect not tested in this work may be the perceived distance between the target object and the discontinuity location; a signed distance-to-discontinuity variable will be included in future investigations. Taken together, the observed effects of discontinuity run counter to the pattern of effects observed in Sinai, et al. (1998). A possible explanation for this contradiction may lie in a critical difference between the two investigations—that the current task unfolds over a nearby spatial extent (on the order of centimeters), whereas the task in Sinai, et al. unfolds over a farther spatial extent (on the order of meters). Further investigations will include action-selection variables to investigate this type of task over a greater spatial extent.

Künnapas (1955b) proposed a framing effect in which the extent of a line will appear to be larger as the surrounding frame decreases in size. In the current task, the target may be considered to be framed by the edges of the table and in some cases by the discontinuity. In such a case, the object should appear to be more reachable as the patch of surface texture that bounds the object increases in size. For example, this hypothesis suggests that objects would look more reachable in the continuous table conditions, as these conditions provide the largest frame for the target object. This hypothesis found partial support in Experiment 1, where the presence of a discontinuity (smaller frame) caused the object to look less reachable (larger distance). However, Experiment 4 showed that the object looked more reachable in the presence of a (far) discontinuity.

In the Oppel-Kundt illusion (Coren & Girgus, 1978; Robinson, 1972), a spatial extent is often seen as being larger than an equally sized referent, if that extent is subdivided (e.g., by a texture discontinuity). This hypothesis also found partial support in Experiment 1, in that the object looked more reachable when the depth extent across the table's surface was subdivided by a discontinuity. This hypothesis breaks down when attempting to interpret Experiment 4's results in that only the farthest discontinuity location affected the perceptual response, meaning that the extent from observer to object was not subdivided in this case, despite making the object appear to be more reachable.

In the horizontal-vertical illusion (Künnapas, 1955a), a vertical extent appears to be longer than an equally sized referent which is bisected by one end of the vertical extent. This hypothesis, like the Oppel-Kundt hypothesis, found partial support in Experiment 1, where objects appeared to be less reachable in the presence of a discontinuity, i.e., the depth extent appeared to be larger when bisected with the horizontal discontinuity. However, unlike the Oppel-Kundt hypothesis, this hypothesis also found support in Experiment 4, where the object appeared more reachable in the presence of the far discontinuity. In this case, the depth extent between the object (near) and the bisection (far) appears to be greater than in comparison conditions, due to this extent effectively "pushing" the target object away from the bisection in the direction of the observer.

Related to the horizontal-vertical illusion hypothesis, though opposing in its predictions, the bisection effect (Finger & Spelt, 1974) causes vertical extents to appear shorter when bisected by a similar extent. Were this hypothesis to hold true, objects would have looked more reachable in the presence of a discontinuity. As in the case of the SSI hypothesis, this hypothesis only found partial support in Experiment 4, insofar as the presence of the (far) discontinuity made objects appear to be more reachable. However, it is not clear if the bisection effect is actually relevant in this case, where the depth extent from observer to target object is not actually bisected. Additionally, if the far discontinuity is to be considered to be bisected, as was considered with regard to the horizontal-vertical hypothesis, then the object should appear to be farther from the observer (less reachable) and closer to the discontinuity.

In the case of surface luminance, the motivating hypothesis was that higher luminance provides more structured light scattered around the target object, allowing the observer to sample from a richer optic structure, potentially allowing the observer to make well-informed perceptual judgments with respect to their capabilities. That is, due to the fact that participants on average overestimate their reaching capabilities by a magnitude of roughly 10% (Weast & Proffitt, 2018; in the current work roughly 20%), higher luminance was predicted to lead participants to show smaller overestimations in their judgements, i.e., perceptual boundaries closer to action boundaries. This hypothesis did not find support in Experiment 1, where no effects of luminance were observed. In Experiment 3, this hypothesis was partially supported, but only in the context of the mean magnitude head movement, where observers were less likely to respond “yes” to objects at all luminance levels as a function of increasing head motion. This decrease in the likelihood of responding “yes” should then indicate a shift of the perceptual boundary (approximately 120% of arm’s length) toward the action boundary (100% of arm’s length). This pattern was reversed in the context of complexity at the highest luminance level, where observers were more likely to respond “yes” to objects at the highest luminance level as a function of increasing complexity. In Experiment 4, the luminance hypothesis found only partial support in subsidiary interactions, where increases in mean magnitude movement at each level of luminance produced decreases in the likelihood of responding “yes” to the reachability task. However, these effects were superseded by higher order three-way interactions where the likelihood of responding “yes” increased as a function of increased head motion and increasing distance. This pattern of results suggests that increases in luminance potentially push the perceptual boundary further away from the action boundary, i.e., increases in the overestimation of reaching capability.

Movement as the Driver of Perception

Taken all together, these results suggest that movement is the primary driver of the perceptual response in this particular task, relative to the environmental variables. Across all four experiments, one or both of the movement parameters drove the perceptual effects alone, or helped to characterize the effects of the environmental variables. In two of the four experiments, including movement parameters significantly improved the explanatory power of the statistical models, indicating that in complex situations (many environmental variables), observer-related dynamics play an important role in the prediction and modeling of the perceptual response. Even in the case of the simpler scenarios where only a single environmental variable was tested (Experiments 2 and 3), despite the dynamic model failing to improve the explanatory power of the static model, including the movement parameters still helped to tell a more nuanced story regarding the perceptual process, evidenced by the observed significant effects. While the model itself does not explain any more of the observed variability, the dynamic model still shows how the total variability is shared amongst the predictors in the model, demonstrating the explanatory power of these observer-related dynamics.

These results also support the hypothesis that perception and action are intertwined, unfolding together in time, where movement reveals visual information (rich optic structure) which informs future movements, and so on. While this work did not support the hypothesis that the deep structure of variability, evidenced by the self-similar dynamics present in the movement data, would help to characterize the perceptual effects above and beyond traditional statistical measures (i.e., the mean and the standard deviation), the results still demonstrate that complexity (multifractal structure) can impact the perceptual response, but in the context of this particular task, the overall amount of movement played a more important role in modeling the perceptual response. Indeed, in everyday tasks, raw movement reveals optic information hidden behind occluding edges (Gibson, 1950), helping the observer navigate his or her environment. Accordingly, the researcher has a responsibility to account for the dynamic interactions of observer and environment when attempting to model perception-action systems.

Regarding Response Times

Very little was found with regard to the modeling of response times in this work. Significant effects were only observed in Experiments 2 and 3, where response times were faster as a function of increased complexity as distance increased. This partially supports the hypothesis that complex movement reveals richer optic structure, potentially leading to higher confidence (and faster responding) in the perceptual judgment. However, this is only speculation and requires systematic investigation. Additionally, the dearth of significant effects is likely due to a lack of statistical power in modeling the response times. The experiments reported in this work were composed of relatively few trials (between 108 in Exp. 1, 135 in Exps. 2-4) compared to what is typical in studies involving response time tasks (Lo & Andrews, 2015; Van Zandt, 2000). Increasing the number of trials in each experiment would increase the statistical power of the reported models, potentially revealing effects missed in the current work.

Summary & Future Directions

This work set out to investigate the effects of three environmental variables, physical distance, surface texture discontinuity, and overall surface luminance, and their roles in the perception of object reachability in virtual reality. Across four experiments, these variables were found to exert differential effects in modeling the perceptual response. These effects were found to be driven by two participant-related movement parameters, average magnitude head movement and complexity of head movement. The current work provides additional support to the ecological theories that suggest that perception and action are two inseparable aspects of the same fundamental process as was proposed by Gibson (1979), and also helps to extend these theoretical foundations to perceptual processes operating in virtual reality.

However, as with any scientific inquiry, this work raises many more questions than it answered. Further investigation is required to answer questions regarding how these surface texture variables impact affordance responses in virtual reality, particularly in the context of magnitude and complexity of exploration. As was identified earlier, an important variable to consider is the distance between the target object and the surface texture discontinuity. This variable may be a step in the direction of refining this investigation, potentially clarifying many of the spatial hypotheses summarized in Table 1. The spatial scale at which this investigation occurred must also be considered and perhaps extended to more closely resemble Sinai, et al.'s (1998) investigation. Future investigations will incorporate an additional action selection component (cf. Weast & Proffitt, 2018), such that stimuli may be presented on a scale larger than that of mere centimeters. Regarding light as being the information for vision, an open question still remains regarding the nature of the structured ambient light. In this work, only surface luminance was manipulated by varying the surface reflectance modeled in the virtual environment while controlling the amount of projected light. The next logical step involves maintaining the surface reflectance and manipulating the amount of projected light. This work will provide the foundation for these extensions, and potentially other inquiries regarding the perception of affordance in virtual reality.

APPENDIX A - FOOTNOTES

[1] There is an active debate over whether everyday perception must be veridical, that is an accurate reflection of the true reality of the environment. For the purposes of this project, this debate will not be addressed and no position will be taken on this issue.

[2] This is another departure from Sinai, Ooi, and He (1998) in that they varied the location of the observer, while the object and the discontinuity remained static from trial to trial. In this case, the observer and the discontinuity will remain static while the object changes location on each trial. While this is a difference worth noting, the relationships between the observer, the discontinuity, and the target object are preserved in that in almost all cases, the discontinuity will occur between the observer and the target object rather than beyond the relevant reaching space.

[3] Because the joint at which a person rotates their arm (i.e., the shoulder) occupies a space above the table (as opposed to at the table's height), a person's effective reach forms a triangle where the distance of the target object from the edge of the table, length a, and the distance from the top surface of the table to the shoulder joint, length b, for the legs of the triangle; the arm's length then becomes the hypotenuse, length c. In order to calculate π-ratios that are based on the participant's effective reach, rather than mere arm's length, the Pythagorean theorem was used to calculate length a given lengths b and c:

$$a^2 = c^2 - b^2$$

[4] Included in the dataset, but not currently reported, are values of the mean and MFW at the level of experimental blocks. This finer grain of measurement should improve the model further, and such an analysis will be included in future investigations.

APPENDIX B – IRB Approval Letter

THE UNIVERSITY OF
SOUTHERN MISSISSIPPI

INSTITUTIONAL REVIEW BOARD
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NOTICE OF COMMITTEE ACTION

The project has been reviewed by The University of Southern Mississippi Institutional Review Board in accordance with Federal Drug Administration regulations (21 CFR 26, 111), Department of Health and Human Services (45 CFR Part 46), and university guidelines to ensure adherence to the following criteria:

- The risks to subjects are minimized.
- The risks to subjects are reasonable in relation to the anticipated benefits.
- The selection of subjects is equitable.
- Informed consent is adequate and appropriately documented.
- Where appropriate, the research plan makes adequate provisions for monitoring the data collected to ensure the safety of the subjects.
- Where appropriate, there are adequate provisions to protect the privacy of subjects and to maintain the confidentiality of all data.
- Appropriate additional safeguards have been included to protect vulnerable subjects.
- Any unanticipated, serious, or continuing problems encountered regarding risks to subjects must be reported immediately, but not later than 10 days following the event. This should be reported to the IRB Office via the "Adverse Effect Report Form".
- If approved, the maximum period of approval is limited to twelve months.
  Projects that exceed this period must submit an application for renewal or continuation.

PROTOCOL NUMBER: 17121903
PROJECT TITLE: It's in the light: The information for vision through the effects of surface luminance and texture discontinuities on object-reachability in virtual reality
PROJECT TYPE: Doctoral Dissertation
RESEARCHER(S): Jonathan Doyon
COLLEGE/DIVISION: College of Education and Psychology
DEPARTMENT: Psychology
FUNDING AGENCY/SPONSOR: N/A
IRB COMMITTEE ACTION: Expedited Review Approval
PERIOD OF APPROVAL: 01/03/2018 to 01/02/2019
Lawrence A. Hosman, Ph.D.
Institutional Review Board

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